A weather-sensitive, spatially-disaggregated electricity demand model for Nigeria

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Abstract

The historical underinvestment in power infrastructure and the poor performance of power delivery has resulted in extensive and regular power shortages in Nigeria. As Nigeria aims to bridge its power supply gap, the recent deregulation of its electricity market has seen the privatisation of its generation and distribution companies. Ambitious plans have also been put in place to expand the transmission network and the total power generation capacity. However, these plans have been developed with essentially arbitrary estimates for prevailing demand levels as the network and generation limits mean actual demand cannot be measured directly due to a programme of almost constant load shedding; the managed and intermittent distribution of inadequate energy allocation from the system operator.

Network expansion planning and system reliability analysis require time series demand data to assess generation adequacy and to evaluate the impact of daily and seasonal influences on the energy supply-demand balance. To facilitate such analysis this thesis describes efforts to develop a credible time series electricity demand model for Nigeria.

The focus of the approach has been to develop a fundamental bottom-up model of individual households accounting for a range of dwelling characteristics, socioeconomic factors, appliance use and household activities. A householder survey was conducted to provide essential inputs to allow a portfolio of household demand models which can account for weather-dependence and other factors. A range of national and regional socioeconomic and weather datasets have been employed to create a regionally disaggregated time series demand model. The generated demand estimates are validated against metered data obtained from Nigeria.

The value of the approach is highlighted by using the model to investigate the potential for future load growth as well as analyse the impact of renewable energy generation on the Nigerian grid.

Declaration of Originality

I declare that this thesis has been completed by myself and that, except where indicated otherwise, the research documented is entirely my own.

Oluwole Oluwadamilola

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To God the Almighty who has blessed me with the talent and opportunity to undertake and complete this research, and to His Son, Jesus, my personal Saviour, through whom I've been comforted in the challenging periods of this work.

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Glossary

AC	Air Conditioner
ADMD	After Diversity Maximum Demand
AEDC	Abuja Electricity Distribution Company
ANN	Artificial Neural Networks
AR	Auto-Regressive
ARIMA	Auto-Regressive Integrated Moving Average
ARMA	Auto-Regressive Moving Average
ASHRAE	American Society of Heating, Refrigerating and Air-Conditioning Engineers
ATCC	Aggregate Technical Commercial and Collection
BEDC	Benin Electricity Distribution Company
BRL	Boland-Ridley-Lauret
CCGT	Combined Cycle Gas Turbine
CDD	Cooling Degree Days
DisCo	Distribution Companies
ECN	Energy Commission of Nigeria
EEDC	Enugu Electricity Distribution Company
EKEDC	Eko Electricity Distribution Company
ELCC	Effective Load Carrying Capability
ENS	Energy Not Served
EPSRA	Electric Power Sector Reform Act
GDP	Gross Domestic Product
GHI	Global Horizontal Irradiance
GIS	Geographic Information System
HDD	Heating Degree Days
HRSG	Heat Recovery Steam Generator
IBEDC	Ibadan Electricity Distribution Company
IKEDC	Ikeja Electricity Distribution Company
IPP	Independent Power Producers
JEDC	Jos Electricity Distribution Company
KDEDC	Kaduna Electricity Distribution Company
KEDC	Kano Electricity Distribution Company
KPI	Key Performance Indicators
LCOE	Levelised Cost of Energy
LDC	Load Duration Curve
LF	Load Factor
LOLE	Loss of Load Expectation
LOLP	Loss of Load Probability
LV	Low Voltage
MA	Moving Average
MBE	Mean Bias Error

MPE	Mean Percentage Error
MERRA-2	Modern-Era Retrospective analysis for Research and Applications, Version 2
MLR	Multiple Linear Regression
MYTO II	Multi-Year Tariff Order II
NASA	National Aeronautics and Space Administration
NBET	Nigeria Bulk Electricity Trading Plc
NBS	National Bureau of Statistics
NDPHC	Niger Delta Holding Company
NEPA	Nigerian Electricity Power Authority
NERC	National Electricity Regulatory Commission
NIMET	Nigeria Meteorological Agency
NIPP	National Integrated Power Projects
NPC	National Population Commission
NPD	Non-Simultaneous Peak Demand
NSO	Nigerian System Operator
O&M	Operation and Maintenance
OCGT	Open Cycle Gas Turbine
ONEM	Operator of the Nigerian Electricity Market
OPF	Optimal Power Flow
PHCN	Power Holding Company of Nigeria
PHEDC	Port Harcourt Electricity Distribution Company
PPA	Power Purchase Agreements
PV	Photovoltaic
REFIT	Renewable Energy Feed-in Tariff
RMSE	Room Mean Squared Error
SO	System Operator
SPD	Simultaneous Peak Demand
TCA	Tropical Continental Air Mass
TCN	Transmission Company of Nigeria
UNDP	United Nations Development Programme
UC	Unit Commitment
UCPF	Unit Commitment Power Flow
WECS	Wind Energy Conversion Systems
YEDC	Yola Electricity Distribution Company

Chapter 1
Introduction

1.1 Thesis Background

Perennial underinvestment in the Nigerian power sector, coupled with its inability to serve demand and an inefficient operating model culminated in the privatisation of the power utility company of Nigeria. This exercise was completed in 2013, and it saw the sale of the government owned generating and distribution companies, with only the transmission company retained by the government. The ensuing energy market is currently in a transitional phase, adopting a purchasing agency structure, where a bulk trader buys power from the power producers and sells to DisCos and other large energy customers.

Although the total installed generation capacity is 12.5GW, the currently available peak generation output of 5GW (40%) is currently unable to meet demand for a population with over 160 million people, with frequent network outages and power cuts prevalent in the network (TCN, 2017). This gap between the capacity and power production is due to gas supply constraints, reservoir constraints, an inadequate transmission network capacity, and maintenance related issues. The limited network infrastructure is unable to effectively transmit generated power, with significant losses experienced in the exportation of power from the south, where most of the generation stations are located, to the demand centres in the north of the country. Although new investments in the distribution networks have been brought about by deregulation, historical funding inadequacy and poor infrastructure in the downstream of the power sector, has resulted in substantial losses being incurred by the new owners (Amadi, et al., 2016). Aggregate technical and commercial losses in the distribution sector varies between 29.4% and 59.1%, with only 25% of the total installed generation capacity available for distribution to consumers (NESI, 2015) (MSEI, 2017). Electricity consumption in the country is currently estimated at 126 kWh/capita, with an electrification rate of around 50% (NBS, 2012). For context, the electricity consumption of South Africa with a quarter of Nigeria's population is 4,198 kWh/capita, while that of the OECD is 7,995 kWh/capita (The World Bank, 2014).

Given the energy supply imbalance, the current power production must be increased, and the network capacity expanded to meet demand. To achieve this, network planning must be as efficient as possible; otherwise it could lead to overestimation of investment, causing the underutilization of generation capacity, or an underestimation of investment, raising energy costs. The power sector road map highlights the government's plan to bridge the energy supply gap, and current transmission expansion projects evidence this objective. However, the funding plans and proposed capacity additions in the power sector roadmap are not supported by a demand study (PTFP, 2013).

The issue of demand is very important in the Nigeria power planning context, as peak demand remains largely unknown due to historical power supply deficits. With power cuts occurring across the network, a definite profile that defines the relationship between demand and time is also unavailable. For a tropical country such as Nigeria, the effect of its warm climate on electricity demand is yet to be explored, as energy use is more a function of generation availability than actual demand.

In mature electricity networks, weather sensitive demand assessments are important in operation planning and generation adequacy evaluations (National Grid, 2010). For electricity networks integrated with renewable energy generation, demand analysis is critical to network system reliability due to the time sensitive nature of variable energy production from renewable resources, as the capacity from alternative energy sources that are scheduled during renewable energy downtimes is determined by the demand during the downtimes. For power systems expansion, accurate demand forecasts underpin network planning as it guides the determination of the candidate generation capacity additions, candidate technology type, cost of energy production and the scheduling of power supply.

As Nigeria is still in the early phase of its network evolution post liberalisation, it is necessary to perform an analysis that quantifies its demand, which should form the foundation for its expansion planning. As the country also aims for a cleaner energy future, it is important to evaluate the impact and value of variable renewable energy generation to its system vis-a-vis the current fossil fuel dominated network to quantify renewable energy benefits for the energy market.

1.2 Research Objective and Scope

The research had the following objectives:

- To determine the key drivers of electricity usage of energy customers in Nigeria.
- To assess the influence of weather on electricity consumption.
- To develop a model that generates unconstrained weather sensitive time series demand data for Nigeria.
- To assess the reliability and cost benefit value of renewable energy generation in Nigeria.

This thesis reports the research methods and results in each of these areas.

1.3 Thesis Statement and Contribution to Knowledge

While there have been national demand forecasting studies done for Nigeria, there is currently no study that accounts for the influence of weather in its analysis. This thesis reports the construction of weather sensitive time series demand data at the national level which incorporates the diverse climatic effects obtained across the country. The generated demand data is then used to explore energy supply in Nigeria, by examining the generation adequacy of the current installed capacity and exploring the reliability and cost benefits of future renewable energy integration with the Nigerian grid.

The unavailability of time series and peak demand data limits the scope of network and investment planning studies for the Nigerian electricity market. The results from this research will be particularly useful to energy related agencies of the government, NGOs and multilateral agencies interested in the Nigeria's power sector, and academics.

1.4 Thesis Outline

This chapter provided and introduction to the thesis. It presented a summary of the current energy market situation in Nigeria and identified the need for a peak demand assessment. It also presents the objectives and knowledge contributions of this research.

Chapter two presents an overview of power systems and provides a discussion on power systems planning. It examines electrical demand and various techniques employed in forecasting it.

Chapter three provides a summary of the Nigerian electricity industry, its power supply features, as well as its demand characteristics.

Chapter four begins with the criteria for the selected methodology used for this project. It presents the results of the survey undertaken as part of this project. Based on the results of the survey, available data from Nigeria and weather reanalysis data, it presents and validates a modelling approach developed to generate weather sensitive time-series demand data.

Chapter five employs the model developed in conjunction with another model for estimating peak demand to construct time series demand data for Nigeria.

The reliability and cost benefit assessment of renewable energy generation for Nigeria are evaluated and presented in Chapter six.

Chapter seven summarises the results from the research and discusses the limitations and impacts of the findings for the Nigerian network. The contribution to knowledge is presented, as well as issues identified for future work.

1.5 Associated Published Work

Oluwole, O, Harrison, G.P & Van Der Weijde, A 2017, 'Modelling electricity and cooling load profiles for domestic customers in Nigeria' 4th International Conference on Energy Meteorology, Bari, Italy.

Chapter 2
Background

This chapter provides a description of electrical power systems and its market structures. It assesses the key considerations for systems planning and analyses approaches that are used for power systems expansion. With demand forecasting being the foundation of expansion planning, an introduction to basic concepts in electricity demand, along with a review of demand forecasting techniques is also presented. Finally, the influence of weather on electricity demand is also discussed.

2.1 Overview of Power Systems

A power system can be described as an integrated network of electrical equipment used to produce and supply electricity consisting of 4 main segments, generation, transmission, distribution and demand as shown in Figure 2-1, which has been adapted from (Sun, et al., 2011). The generation segment is made of companies that generate and sell electrical energy. The transmission segment is made up of the companies that own the power transmission equipment including cables and transformers.

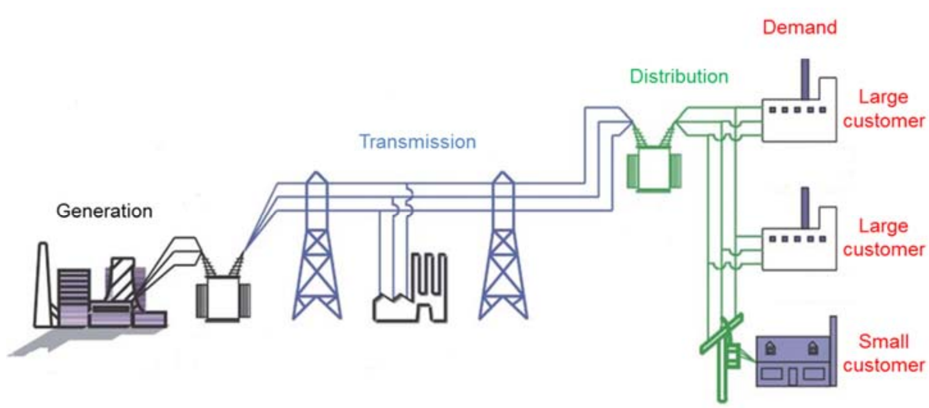


Figure 2-1: Structure of a typical power network

The distribution segment is made up of companies that own the distribution equipment for supplying electrical energy to the end users. The demand segment is made up of small and large customers that purchase electrical energy from the distribution companies or energy suppliers. Small customers are typically connected to a distribution company, while large customers may be either connected to the distribution or transmission network.

2.1.1 Power Systems Structures

The demand for increased efficiency and lower energy prices through competition among the power sector stakeholders has seen the deregulation of some power utility companies, with a migration from traditional network structures to competitive restructured markets (Stoft, 2002). In a traditional network structure, the power company is run as a vertically integrated utility that consists of the generation, transmission and distribution networks and functions as a monopoly. In this structure as shown in Figure 2-2, customers purchase electrical energy directly from the power utility through the distribution company.

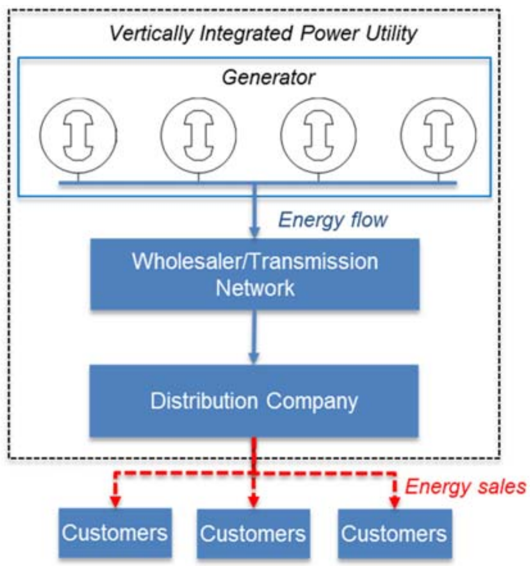


Figure 2-2: Traditional power network structure

Transition from traditional power network structures has seen the evolution of power markets with different market participant competition models namely, the purchasing agency, wholesale competition and retail competition (Kirschen & Strbac, 2004). In the purchasing agency model, the vertically integrated company is disaggregated and sees private generators sell their energy directly to a wholesaler, who in turn sells the energy to private DisCos as shown in Figure 2-3. A regulator determines the energy rates established by the wholesaler to ensure energy cost minimisation for customers. In this structure, competition exists only among the private generators. This is the current structure of the Nigerian electricity market, the focus of this study. In the wholesale competition structure, the wholesaler entity is absent, with energy purchases occurring directly between distribution and generation companies. A higher level of competition occurs in this structure between generators as energy prices are determined solely by the market interaction of demand and supply, while distributed energy prices remain regulated. In the retail competition structure, which has the highest level of competition, it sees retailers purchase energy directly from generators and sell to their customers, while engaging the distribution and transmission infrastructure for energy dispatch. The distribution and transmission network function as monopolies providing energy evacuation services, with transmission use fees paid by the retailers.

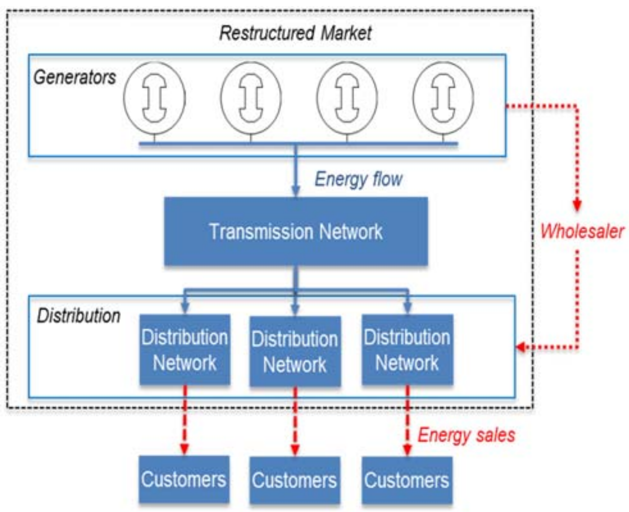


Figure 2-3: Restructured market - Purchasing Agency

The need for improved network efficiency has seen the adoption of restructured markets in developed countries, while the objective of attracting private capital to fund power sector expansion in developing countries has catalysed their power market restructuring (Shiu & Lam, 2004) (Wu, et al., 2006) (Ikeme & Ebohon, 2005). There are benefits and challenges to both the traditional structure and the restructured markets, with the main challenge of the traditional structure stemming from a lack of incentives to the regulator to improve efficiency (Stoft, 2002) (Cubbin & Stern, 2006) and that of restructured markets being the profit interests of shareholders versus regulatory cost minimisation objectives (Maghouli, et al., 2009) . The centralisation of the funding and capital budgeting decisions in the traditional structure sees an alignment among administrators of the network segments which assists with ensuring its viable operation (Jamasb & Pollitt, 2005). While some level of cost minimization and electricity price reduction may be achieved through the competition between multiple private companies seeking cost efficiency, it also depends on the level of development of the country (Bacon & Beasant-Jones, 2001). The cost of capital and regulatory costs to private investors operating in developed restructured markets creates a conflict between tariff reduction and energy efficiency objectives, while energy price increases are required signals for private investment in developing markets (Nagayama, 2009). While traditional structures might be inefficient, the improved operational efficiency of the individual restructured market participants might not necessarily provide an advantage over its coordinated network operation (Steiner, 2000) (Jamasb & Pollitt, 2005) (Zhang, et al., 2008). For capacity expansion, an overestimation of demand forecasts in traditional structures that leads to overbuilding results in customers bearing its cost (Kirschen & Strbac, 2004). In the restructured market, profit maximisation incentivises participants to expand capacity on a marginal growth in demand basis which reduces the risk of overbuilding (Foley, et al., 2010). When overbuilding does occur in restructured markets, while there is a belief that this cost is borne solely by shareholders, Stoft (2002), argues that this risk is priced into the cost of private capital and ultimately borne by the customers. Power systems planning in a traditional structure is coordinated by a single body across its segments, however, in a restructured market made up of competing individual objectives, the lack of alignment in the planning process among market participants creates uncertainty in expansion planning, as conflicting expansion objectives might result in the suboptimal deployment of capital.

2.2 Power Systems Planning

Power system planning can be described as the development and design of strategies to efficiently supply quantified electrical demand from available energy resources. Power system plans cover a wide range of analysis but are broadly grouped into 4 main activities: demand, power generation, transmission and distribution. Planners will typically have to make a choice from a list of options to solve a power system problem. For example, in generation system planning, options can include deciding between building a new power plant and importing power. The selected choice or group of choices made from the options available to the planner creates the plan.

Power systems plans vary in duration, from short term plans which are less than five years (Central Electricity Authority, 2016), to medium term plans which are typically between five to ten years (NB Power, 2015) and long term plans which can be longer than ten years (Thailand Ministry of Energy, 2015). Based on the futuristic nature of planning, quantifying and making provisions for the impact of likely and unwanted future events on the selected plan, is an important step. These uncertainties in planning typically increase with the length and scope of the plan. The system operator plans to meet hourly estimates of demand and schedule generation dispatch accordingly, while accounting for uncertainties in hourly and weekly demand and generation availability. The distribution network planner's primary interests include the improvement of network performance, reduction of losses, maintenance of voltage quality and reducing investment costs while also accounting for in demand growth uncertainties in the short term, the impact of electrical consumer technologies and those related to the variability from integrated renewable energy generation. Generation and transmission system planning, the focus of this research, which occurs over a long-time frame due to technology considerations in reducing investment costs, is considered dynamic, while shorter term planning (≤ 1 year) is considered static (LaTorre & Cruz, 2003). Generation technologies with low operating and high fixed costs, such as hydro and nuclear, require longer build times than high operating and lower fixed costs generation technologies such as a gas turbine.

Uncertainties regarding such long-term projects include: load growth, fuel prices, policy changes, and technological advancements. While aiming to ensure an efficient supply of power and avoiding network congestion, the transmission planner faces uncertainties with regards to the locational challenges of new generation projects and the spatial coordination of intermittent renewable energy projects (Munoz, et al., 2017). The evaluation of different options, as well as the analysis of the anticipated uncertainties, will determine the measure of “goodness” used to describe the objectives. Objectives of power system planning are typically defined regarding the following considerations (Merrill & Wood, 1991),

1) Economic: These relate to the economic consideration for the generation and distribution of energy. They include impact assessments of new energy technologies, network expansion costs, pollution costs, energy imports and exports, and energy prices on the economy and consumers.
2) Environmental: These relate to the impact of the energy plan on the environment such as carbon emissions from fossil fuel generation, aquatic impact of hydro and offshore power generation technologies. It also includes siting of generation stations and an assessment of the passage rights for overhead transmission lines and cables.
3) Financial: These relate to the investment considerations for a power system plan. These include the capital expenditure requirements for building and retiring generation power plants, power system operational, expansion and reinforcement costs.
4) Quality: These relate to ensuring the adequacy of electrical energy in supplying demand. These include maintenance scheduling, contingency planning for system faults and generation outages, critical peak demand projections and network planning to accommodate new generation projects.
5) Societal: These relate to the impact of the energy plan on the society. These include energy efficiency considerations, fuel diversity and renewable energy expansion, energy conservation, and government policies.

While some objectives are easier to quantify than others, in some cases for the same plan, objectives may be in direct opposition to each other. With multiple objectives, a planner must prioritise the objectives due to the difficulty of optimally satisfying each one. Based on the multi-objective nature of most transmission system plans, planners typically rely on modelling tools to obtain optimal solutions to evaluate the objective problem. These models largely fall under two categories, mathematical and heuristic models. Mathematical models seek to the solve the optimization problem as a mathematical calculation with an objective function subject to different limits imposed on the system to be expanded, e.g., determining the cheapest generator from a group of generators to supply power during a certain period subject to the capacity of generators and demand. Mathematical methods include linear programming (Chanda & Bhattacharjee, 1994), dynamic programming (Garcıa-Bertrand & Minguez, 2017), non-linear programming (Youssef & Hackam, 1989) and mixed-integer programming (Zhang, et al., 2012). Heuristic models use rule guided algorithms to search for optimal expansion routes within the framework of the expansion problem, with solutions obtained when a better plan cannot be achieved by the algorithm. Heuristic modelling applications to power system expansion planning include constructive heuristic algorithm (Sanchez, et al., 2005) and probabilistic load flow algorithm (Nikmehr & Ravadanegh, 2015). While both optimization models have their unique limitations, including long computation times and non-convergence to an optimal solution for mathematical models, and unreproducible nature of heuristic approaches to varied characteristics of the same power system, they provide planners with powerful computational tools in evaluating the objective values of each plan (LaTorre & Cruz, 2003).

Power system planning analysis typically occurs over a two-stage process as shown in Figure 2-4. The development of a database of projected demand and energy supply data required for expansion occurs in the first stage, and in the second stage, an integrated analysis that allows the planner to investigate the impact of the expansion plan on the network. Multiple scenarios of this analysis can then be executed to allow the evaluation of various network expansion configurations. The aim of expansion planning is to ensure a least cost plan that guarantees adequate transmission capacity to meet demand while operating a transmission network that is reliable. This requires an assessment of electrical demand, energy supply technology, economic evaluation, network technical considerations and impact analysis.

The following sections looks at some of the typical considerations for the system planner.

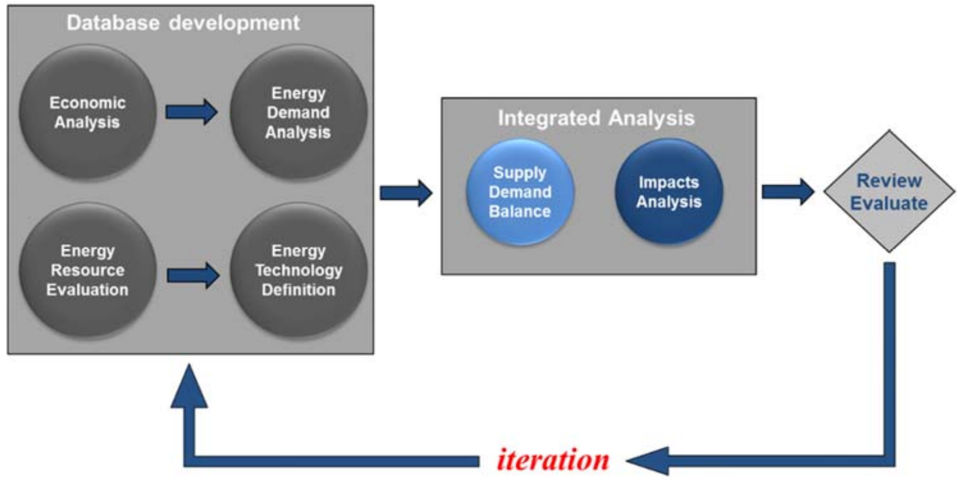


Figure 2-4: Typical process of power system planning (IAEA, 1984)

2.2.1 Electrical Demand

Forecasting of electrical demand is a critical step in generation system planning. This estimation requires forecasting electrical demand and predicting its variability over a given period. This will also assess the economic and sectoral drivers of electricity demand to identify consumption patterns that can be used to forecast future demand. Forecast periods of interest include the weekly, monthly and seasonal periods of the years of analysis. Demand quantities to be forecasted include the peak demand (W) and the energy to be consumed within the period of study (kWh).

In demand forecasting, the main demand uncertainties faced by planners include stochastic and future related uncertainties. While demand forecasts can be estimated, the random nature (stochastic) of electrical demand means its response to unplanned events is uncertain. Examples of such events include increased electrical demand from televisions as customers tune in to watch an important programme, or the impact of weather on demand. In 2001, the conclusion of a UK television programme, EastEnders, saw a spike in demand of 2.3GW (Drax, 2016), while extreme unpredicted weather conditions across any of the seasons in the forecasting period can significantly increase demand (Thorton, et al., 2017). The random nature of demand also means future projections can either be overestimated or underestimated. Expansion plans based on overestimated projections result in a suboptimal use of resources, with energy customers bearing the cost of expansion. Underestimation increases the risk of power system unreliability and can result in power shortages due to inadequate generation capacity in the events of generation station outages.

2.2.2 Energy Supply Technologies

The selection of power generation candidates is dependent on various factors including fuel resource availability, fuel resource prices, technology advancement, regulatory policy objectives and cleaner energy targets. Figure 2-5 shows the projections of the global share of net electricity generation by technology type. For reference, the 2015 global net energy generation was 24,255 TWh (International Energy Agency, 2017). The net energy generation is the difference between the energy produced and consumed by a power plant.

System planners must determine an optimal mix of generation supply type that provides adequate electricity and meets the planned objectives. Currently fossil fuel technology is the current market leader with 66%, driven by coal and natural gas. 69% of global coal electricity production is from China, USA and India, while 42% of the global natural gas electricity market is dominated by the USA, Russia and Japan. 23% of the global energy supply market is provided by renewables, which is currently dominated by a 43% contribution from China, USA and Brazil (International Energy Agency, 2017).

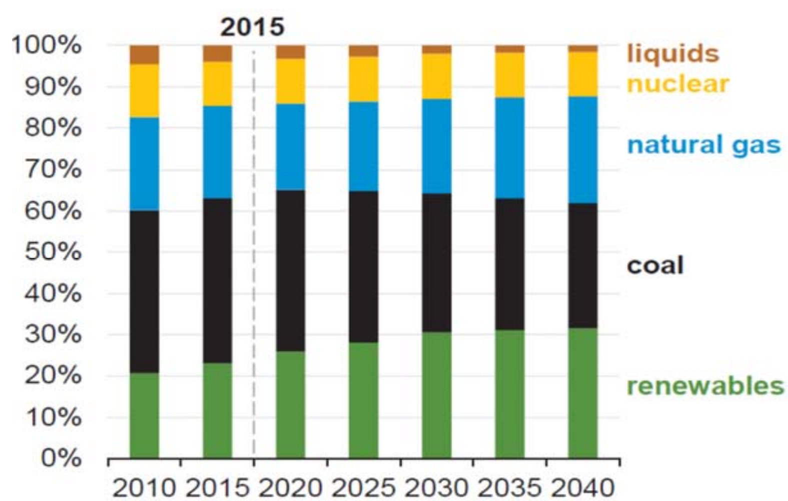


Figure 2-5: Global share of net electricity generation by technology type (U.S Energy Information Administration, 2017)

The past decade has seen a transition in the global energy resource attitudes with countries aiming to produce cleaner energy and reduce carbon emissions. This change, driven by increased renewable energy generation, has been supported by new investment, technology cost declines and high uptake in developing countries (World Energy Council, 2016). The current available renewable energy technologies include solar, hydropower, wind, marine, geothermal and bioenergy. Going forward, renewable energy generation, aided by technological advancements and a favourable regulatory climate, is projected to have a steady year-on-year growth and catch up with coal, the current energy technology market leader in 2040. However, limitations including non-dispatchability of renewables, a lack of smart control infrastructure for network security management (Robertson, et al., 2018), energy price uncertainty stalling submitted long term projects (Menanteau, et al., 2003) and inadequate government incentives for renewable energy (Byrnes, et al., 2013) might hinder its projected growth.

Global carbon emission targets will necessitate a projected reduction in energy generation from coal, however, low prices and a saturated supply market, will see a projected increase in natural gas consumption (World Energy Council, 2016). However, the energy security objectives of import dependent nations to limit their exposure to gas price volatility might constrain the projected growth of natural gas consumption, as this is expected to cause a marginal increase in global nuclear generation (Adamantiades & Kessides, 2009).

2.2.3 System Energy Costs

Cost Analysis

The costs involved in building a new generation plant are the power generation cost, the operating cost of generating electricity and the capital investment cost, the cost required to build the power plant. The power generation cost can be divided into two categories, fixed and capital costs, costs incurred by the power plant independent on the energy generated, and the variable costs, the costs incurred by the power plant dependent of the amount of energy generated. Fixed costs include the cost of the power generation equipment, fixed fuel costs e.g., equipment used for fuel storage and the fixed operation and maintenance (O&M) costs such as salaries. The variable costs include the variable fuel and variable O&M costs. Other variable costs include the carbon emission costs which will apply where carbon taxes or trading schemes exist. Table 2-1 shows estimates for the fixed and variable costs for different power generation technologies.

Table 2-1: US estimates of power plant capital and operating costs (U.S Energy Information Administration, 2016)

	Costs (2016$)			
Technology	Nominal Capacity (MW)	Overnight Capital Cost ($/kW)	Fixed O&M ($/kW-Yr.)	Variable O&M ($/MWh)
Ultra-Supercritical Coal	650	3,636	42.1	4.6
Combined Cycle Gas Turbine	702	978	11	3.5
Advanced Nuclear	2,234	5,945	100.28	2.3
Biomass	50	4,985	110	4.2
Hydroelectric[1]	500	2,936	14.13	0
Onshore Wind	100	1,877	39.7	0
Solar- Photovoltaic	150	2,671	21.8	0
Battery Storage	4	2,813	40	8

Different fixed and variable costs combinations can be seen, with some technologies having high fixed and low variable costs e.g. Nuclear, and high fixed and high variable costs, e.g. Biomass and Coal. Wind and Solar have no variable O&M costs as they are fuelled from renewable energy sources. To make comparisons between different generation technologies, the levelized cost of energy (LCOE) is used. The total costs related to a power generation station are not recovered upfront, but rather over the proposed lifetime of that project.

The annual value of the total costs of generating energy in each year of the study is calculated to obtain the LCOE as show in Figure 2-6. The LCOE can be evaluated using (International Energy Agency, 2010):

$$LCOE = \frac{\sum_{t=1}^{n} \frac{I_t + M_t + F_t + C_t + D_t}{(1+r)^t}}{\sum_{t=1}^{n} \frac{E_t}{(1+r)^t}} \tag{2.1}$$

where I_t is the capital cost including financing in year *t*, M_t is the O&M cost, F_t is the fuel cost, C_t is the carbon emissions cost, D_t is the plant decommissioning cost, E_t is

[1] Hydroelectric costs are represented by 2012 data.

the electrical energy generated, r is the discount rate used to evaluate the present worth of anticipated future revenues on the project, and n is the lifetime of the project.

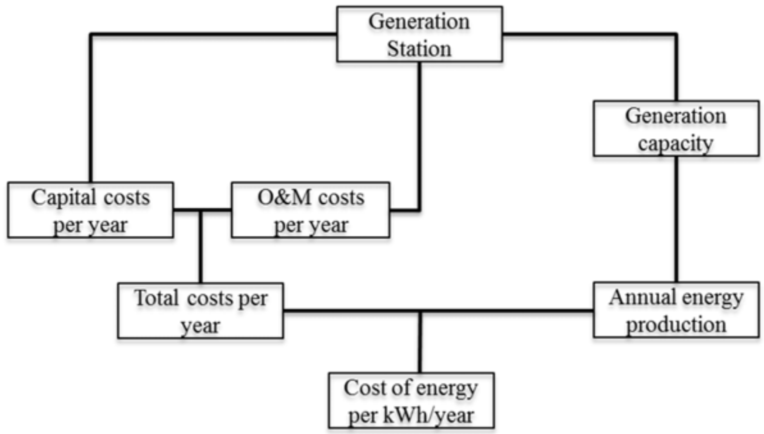


Figure 2-6: LCOE Estimation (The European Wind Energy Association, 2009)

Since LCOE represents the annual cost associated with a power project, it allows for the comparison of different generation technologies with different capacities, lifetimes, and financial returns. For example, Figure 2-7 shows the 2015 LCOE comparison between combined cycle gas turbine, coal and nuclear power stations at three discount rates (3%, 5% and 10%). In this example, nuclear energy production is most sensitive to changes in the discount rate, even though it is the cheapest energy source compared to the others at the lowest discount rate.

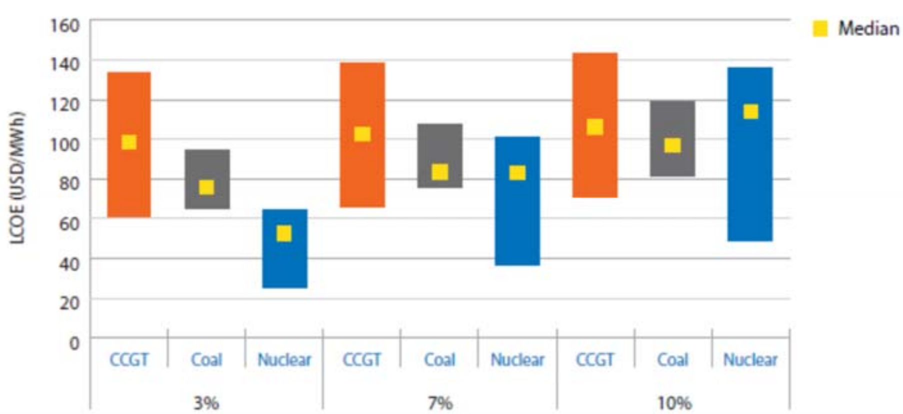


Figure 2-7: LCOE ranges for baseload technologies (International Energy Agency, 2015)

While LCOE is used for cost comparison independent of demand, generation expansion requires production cost analysis of the candidate technologies required to supply demand. This is achieved either using screening curves or through solving economic dispatch or unit commitment problems. Screening curves are used to compare between technologies by expressing total costs as a function of the amount of energy to be produced to serve demand at a period. However, screening curves are limited in their application as they assume generators will always be on and ignore operational requirements of generation plants, such as maintenance and outages, which are not factored into the analysis.

The economic dispatch problem is one that seeks to identify the optimal combination of the units of generation plants required to supply demand most economically at a given time. In simple terms, it requires determining which generator units to switch on and switch off at different times to ensure economical supply to the demand. Although solved mathematically as an optimisation problem, Figure 2-8 shows a simple example with a generator with 3 units required to supply demand throughout the day. The plot shows the available capacity for power production from each unit and not the power supplied. All units in this example have the same minimum and maximum capacities, with a maximum capacity limit of 600MW. In increasing order, unit 1 is the cheapest unit, followed by units 2 and 3, respectively. Based on production costs analysis, the most expensive unit will be required to run for the least amount of time, with the cheapest unit required to run for the most amount of time, and intermediary cost units running when the capacity limits of cheaper generators have been reached. This rule is also required to ensure that the combinations of supplying units meet the demand. In the example shown, only unit 1 is required to run until 11am when the demand exceeds 600MW, and then unit 2 is switched on. When demand exceeds 1200MW at 5pm, unit 3 is switched on. However, this presents a complex problem considering that the multiple generators on transmission networks consist of different technologies, have different capacities and different operating costs. This is further complicated by the technical limitations of each operating unit, such as ramp rates, the time limits required to switch a unit on or off, fuel and renewable energy resource availability, and other units that must always supply power, and thus becomes a unit commitment problem. For power system expansion analysis, optimisation tools are used mathematically solve the unit commitment problem. This is discussed further in Chapter 6.

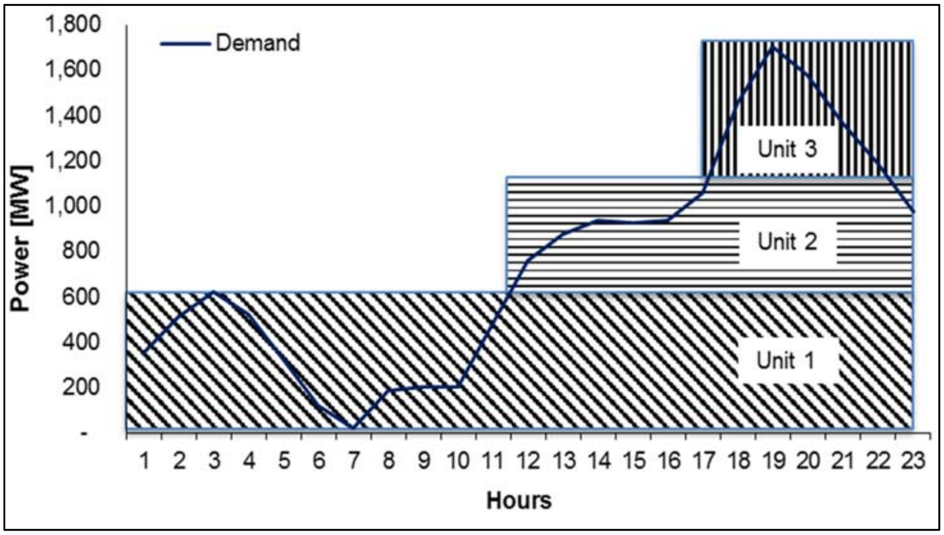


Figure 2-8: Simulated dispatch order (Robertson, 2018)

<u>Energy Production Cost Analysis</u>

Energy production cost analysis requires estimating the cost involved from generating energy given the available energy resources in the planning location by each candidate technology type. Below are some of the factors that impact the production cost analysis.

1) Production Cost: Quantifying the potential amount of energy that can be generated is the first step in this analysis. For example, the availability of natural gas will determine the amount of electricity that can be generated by gas turbines. The distribution of energy resources is a major determinant in the energy supply options and energy mix of a location. For renewable energy sources, this would involve estimating the amount of energy that can be successfully converted by the candidate technology to electrical energy. For example, the total wind energy in a location cannot be converted to electrical energy, therefore the capacity and efficiency of candidate wind turbines will determine the amount of energy that can produced. The efficiency η of power plant is obtained using:

$$HR = \frac{Input\ Energy}{Output\ Power} \tag{2.2}$$

$$\eta = 3412\ Btu/HR \tag{2.3}$$

where HR is the power plant heat rate (Btu/kWh), *Input Energy* is the fuel energy used to generate electricity (Btu/hr) and the *Output Power* is the power produced from the power plant (kW). It remains common for "Btu" to be used in relation to heat rate, but equivalent "kWh" exists. The efficiency of the technology equipment will determine the amount of useful energy that can be generated based on the available fuel source.

Table 2-2: Conversion efficiencies by plant type (U.S Energy Information Administration, 2010) (U.S Energy Information Administration, 2017) (New South Wales Government, 2010) (GE, 2018)

Technology	Fuel Type	Efficiency (%)
Steam Generator	Coal	34
Open Cycle Gas Turbine	Natural Gas	30
Combined Cycle Gas Turbine	Natural Gas	50-62[2]
Advanced Nuclear	Uranium	33
Geothermal	Geothermal	16
Conventional Hydroelectric	Water	90
Solar PV	Solar	15-20
Wind	Wind	45

Efficiency factors of selected technology types are shown in Table 2-2. An open-cycle gas turbine (OCGT), with an efficiency of 30%, consists of a gas turbine connected to an electric generator via a shaft. By connecting a heat recovery steam generator (HRSG) to the OCGT, additional power can be generated by using the recovered heat to power a steam turbine generator. This creates a combined-cycle gas turbine (CCGT), which has an efficiency of about 60%, thereby increasing the electrical energy that can be generated from the same amount of fuel.

The energy or variable cost of a generator can then be calculated using (Sullivan, 1977):

[2] CCGT maximum efficiency value based on General Electric HA 605MW Bouchain plant in France.

$$EC_G = FC_G + OM_G \tag{2.4}$$

$$FC_G = HR_G \times f_G \times E_T \tag{2.5}$$

Where EC_G is the energy production cost, FC_G is the fuel cost, OM_G is the operation and maintenance cost, HR_G is the heat rate of the generator, f_G is the unit fuel cost, and E_T is the estimated energy to be produced.

2) Availability: The need for periodic maintenance, and the possibility of generator unit faults means generators will not be constantly available to supply power. The total period a generator will be available needs to be estimated to calculate the energy costs. The unitless effective availability EA can be obtained using (International Atomic Energy Agency, 1984):

$$EA = (1 - POR) \times (1 - EFOR) \tag{2.6}$$

$$POR = \frac{SMH}{PH} \tag{2.7}$$

$$EFOR = \frac{FOH}{SH + FOH} \tag{2.8}$$

where *POR* is the planned outage rate, *EFOR* is the equivalent forced outage rate, *SMH* is the scheduled maintenance hours, *PH* is the total hours in the analysis period, *FOH* is the forced outage hours for when the plant will be shut down due to faults, and *SH* is the supply hours when the generator supplies energy. The maximum expected energy produced *EP* (Wh) can then be estimated using:

$$EP = EA * PH * P_G \tag{2.9}$$

where P_G is the power plant capacity (MW).

3) Capacity Factor: Having quantified the energy that can be produced, the actual energy that will be produced can be estimated based on historical capacity factors of that technology type in the planning location. The capacity factor of

a power plant is the measure of the usage of a generator and can be calculated using:

$$Capacity\ Factor = \frac{\sum_{t=1}^{T} E_t}{E_{max}} \tag{2.10}$$

where E_t is the energy produced (Wh) over time T (hrs), and E_{max} is the maximum energy (Wh) over period T that can be produced from the generator based on its capacity.

Figure 2-9 shows the UK embedded solar power generation for 2017. It can be seen the power generation from embedded solar was not at maximum capacity at any time during the year, with its maximum power production occurring during the summer months due to increased solar irradiance. Constant maximum power production from a generator is not feasible due to the energy production cost maintenance schedules, fuel availability, and pollution or technical curtailment[3]. The capacity factor for this technology type was 9.8% in the UK for 2017. The capacity factors also serve as an indicator to the mode of the generator operation, which is determined by the energy production cost.

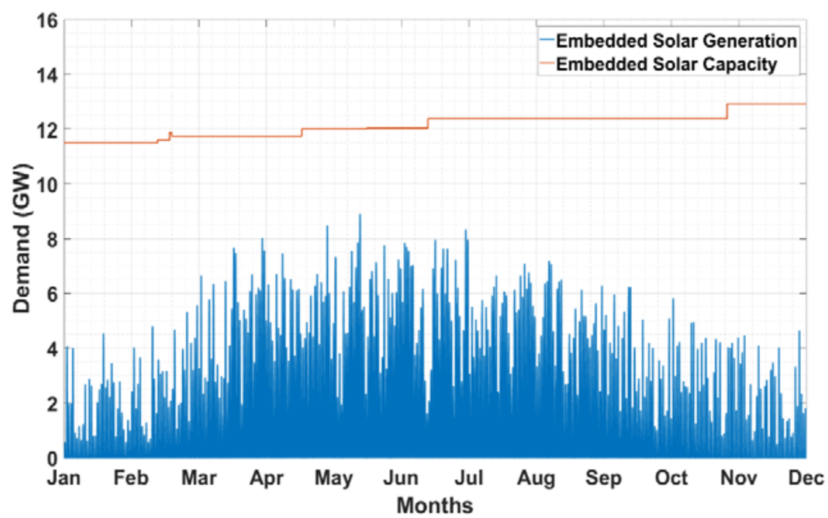


Figure 2-9: UK embedded solar power generation in 2017 (National Grid, 2018)

There are three main modes of operation: base load generators which operate for most of the year except during periods of maintenance; peaking generators

[3] Curtailment: The compulsory shutting down of power plants to prevent power system instability.

which operate during the periods of maximum demand and intermediate generators which operate in between the base load and peaking generators as the demand fluctuates between both.

Table 2-3 shows the typical capacity factor for generation operation modes. Generators with the lowest energy costs are typically used to supply the base load, with higher energy costs generators called upon as the demand increases.

Table 2-3: Typical Capacity Factor Ranges (IAEA, 1984)

Operation Mode	Capacity Factor (%)
Base load	50-70
Intermediate	20-40
Peaking	0-10

4) Dispatch order: This refers to the system cost minimization ranking of generator units to be dispatched. This categorisation is determined by the energy costs of the generating units, which include the cost of running and starting up. The start-up cost is the cost required to get a generator to generate power from a shutdown state. Diesel and OCGT generators start up quickly and have low start-up costs, however, larger thermal units, require significant heating for steam production which takes time, and are therefore costly.

   Typically, nuclear, hydroelectric, wind and solar have the lowest energy costs (Table 2-1), and would be dispatched first, and as the demand increases, other higher cost generators will be dispatched. The availability of renewable energy resources, and supply-demand balancing will determine their use in supplying base load. Figure 2-10 shows a simulated one-day dispatch order for the UK. The generator supply is stacked in increasing cost order by technology type. Nuclear is dispatched throughout the day at constant output, followed by wind (onshore and offshore) based on availability then fossil fuel plants and other generator types. While hydroelectric stations have low variable costs, their dispatch is complex due to resource availability (reservoir levels) and other factors including revenue considerations.

5) Reliability: To ensure system reliability, additional generation capacity is needed in the event of unexpected demand surges or the forced outage of

generators, and to also accommodate power transmission losses. Due to the start-up time involved in getting a generator from an inactive state to full power capacity, the generators needed to provide this redundancy will be required to have quick power supply responses, and so will need to be spinning i.e. synchronised to the grid. This provision is known as the spinning reserve. Generators that can be quickly started might not be required to be spinning and this reserve is called non-spinning or static. The generating unit energy cost determines the participation of the unit in providing this service, which then requires strategic reserve allocation by the system planner. Allocation of spinning reserve to only the lowest cost generator units will increase the system energy production costs, as higher cost units will be required to supply the demand usually met by the lower cost units. Allocation to only the higher cost units will also drive up the system energy production costs, as the commitment of the higher cost units will prevent the dispatch of lower cost units during periods of low demand (Kirschen & Strbac, 2004) (IAEA, 1984). Spinning reserves are typically distributed across the system generators (Prada, 1999).

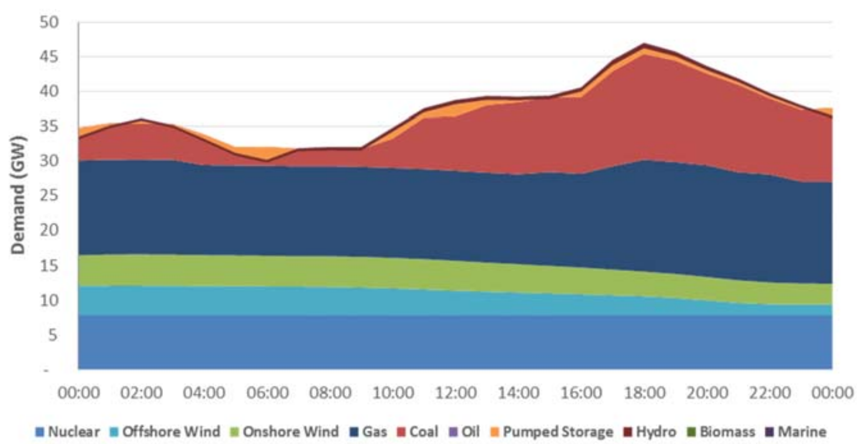


Figure 2-10: Simulated dispatch order for the UK (Robertson, 2018)

2.2.4 Technical System Considerations

The power system planner aims to develop an optimal expansion plan that minimizes costs and ensures the power system remains reliable, which poses an economic and technical problem. Over the projected planning horizon, the plan must ensure adequacy of the transmission network in accommodating the growth in generation capacity to supply the forecasted growth in demand. To achieve this, it will require the timely addition of new generation and transmission network infrastructure, while also ensuring the power flow on the planned network respects technical requirements such as power supply and demand balance, generation reserve provision, frequency and voltage stability and transmission line thermal limits. The power flow component ensures that the aggregate sum of power generation injected into the transmission network is equal to the total demand plus network losses.

In power system expansion modelling, this is typically solved as a mathematical problem with cost minimization as the objective function (economic), subject to technical system constraints, and termed the optimal power flow (OPF). The mathematical formulation of an OPF problem is presented using (Wood, et al., 2014):

Minimize: $$f(x, u) \tag{2.11}$$

Subject to: $$w(x, u) = 0 \tag{2.12}$$

$$g(x, u) \leq 0 \tag{2.13}$$

where u is a vector of independent parameters containing the generator cost function parameters, the generator power capacity limit and all fixed parameters of the transmission network, and x represents the dependent variables of the transmission network. Equation (2.12) gives the equality constraints representing the power flow equations and Equation (2.13), the inequality constraints, representing the real and reactive power limits of each generator.

For a transmission network of *N* buses, the objective function to be minimized is the operating cost of total generation (Wood, et al., 2014):

Minimize: $$\sum_{i=1}^{N_{bus}} F_i(P_{gen,i}) \tag{2.14}$$

where $F_i(P_{gen,i})$ is the cost function of the generator at bus i, and $P_{gen,i}$ is the real power generation.

A transmission network of *N* buses obeys 2*N* complex nodal equations representing the real and reactive power flow in the lines *L*. Using a complex power notation, $P_{gen,i}(V, \delta) - jQ_{gen,i}(V, \delta)$ representing the power injection at each bus, the real and reactive power equality constraints can be presented using (Dommel & Tinney, 1968).

$$P_{gen,i} - P_{load,i} = \sum_{l=1}^{L} P_l(V,\delta) \tag{2.15}$$

$$Q_{gen,i} - Q_{load,i} = \sum_{l=1}^{L} Q_l(V,\delta) \tag{2.16}$$

where $P_{gen,i}$ and $Q_{gen,i}$ are the real and reactive power generation on bus *i*, $P_{load,i}$ and $Q_{load,i}$ are the real and reactive power demand, and V and δ are the vectors of voltage magnitude and voltage angle at either end of line *l*.

Having satisfied the power flow constraints, inequality constraints are then included in the problem formulation. These include the generator real and reactive power limit constraints:

$$P_{gen,i}^{min} \leq P_{gen,i} \leq P_{gen,i}^{max} \tag{2.17}$$

$$Q_{gen,i}^{min} \leq Q_{gen,i} \leq Q_{gen,i}^{max} \tag{2.18}$$

where $P_{gen,i}^{min}$ and $Q_{gen,i}^{min}$ are the minimum real and reactive power generation on bus *i* and $P_{gen,i}^{max}$ and $Q_{gen,i}^{max}$ are the maximum real and reactive power generation.

Voltage magnitude constraints:

$$V_i^{min} \leq V_i \leq V_i^{max} \tag{2.19}$$

where V_i^{min} and V_i^{max} are the minimum and maximum voltage magnitudes on bus *i*

Thermal limit constraints:

$$S_l \leq S_l^{max} \tag{2.20}$$

where S_l and S_l^{max} are the thermal flow and the maximum thermal limit.

As well as operational settings, OPF has been used extensively in power network expansion planning with a focus on different network objectives including, multi-area expansion planning with reliability constraints (Khodaei, et al., 2012), the impact of risk aversion on generation and transmission investment (Munoz, et al., 2017), bi-level assessments of transmission investment impact on energy markets (Garces, et al., 2009) and energy producers (van der Weijde & Hobbs, 2012), and assessments of transmission expansion under uncertainty (De la Torre, et al., 1999), (Ruiz & Conejo, 2015).

2.2.5 Planning Approaches

In the traditional network structure, coordinated systems planning is executed by the utility company with a typically least expansion cost objective. However, since energy prices are regulated, the absence of competition fosters the lack of operational efficiency which means the least cost energy production analysis might be overlooked during expansion planning. The benefit of planning in this structure is the centralised coordination and scheduling of expansion activities, which reduces the risk of stranded power generation from new projects due to uncertainty in the expansion of the transmission network which can occur in a decentralised process. Traditional network planning allows for a linear approach to network operation analysis that assesses the worst-case operations condition in the event of network equipment outage, known as the N-1 or N-2 criterion (Prada, 1999). Political involvement in the energy pricing regulatory process can result in the detachment of energy use prices from energy generation costs, leading to the over-subsidisation of energy and/or expensive energy (da Silva, et al., 2016). Regulatory initiatives to reduce carbon emissions and fuel import price volatility exposure might impact the decision on energy supply candidates (El Chaar & Lamont, 2010), (Rogner, 2013).

In a restructured market, the regulator's objective is to ensure a competitive and sustainable electricity market with reliable power supply. However, the conflicting objectives of market participants across its segments creates uncertainties that hinder expansion planning (Buygi, et al., 2003). This situation is particularly acute in developing countries adopting a restructured market, with uncertainties affecting the entire value chain of the energy supply market (Eberhard & Gratwick, 2011) (International Energy Agency, 2014) (U.S Energy Information Administration, 2017). For instance, the investors in new power generation stations might be deterred by the absence of guarantees regarding the timely connection of new transmission lines to export generated power. Delays in the provision of necessary fuel transportation infrastructure will also affect the installation of new projects. Changes in regulatory policy regarding energy prices and market entry might affect the profitability and construction of new projects. Expansion funding mismatches between generation and transmission will also create planning uncertainties. Inadequate transmission investment in a congested network might create locational generator monopolies in regions with power flow constraints (Wallace & Harrison, 2003). Uncertainties in load forecasts due to technology and adoption of demand side management by networks can also affect expansion planning.

Due to the myriad complexities and uncertainties involved in restructured markets, non-linear methods are used to evaluate the risks involved in power system planning. Different probabilistic approaches are used to analyse uncertainty and assess the risk involved in planning, including probabilistic modelling of the peak demand (Chen, et al., 2008) (Nikmehr & Ravadanegh, 2015), modelling that analyses the reliability metrics e.g. energy not supplied (ENS) of different plans (Aghaei, et al., 2014) (Dehghan, et al., 2016), decision trees that evaluate different futures (Dekrajangpetch & Sheble, 2000), and the robust scenario modelling of each plan (Bouffard & Galiana, 2008) (Chaudry, et al., 2014).

For scenario analysis, the planner estimates the likelihood of the uncertainty of a plan occurring and quantifies this by assigning a value to each objective if the uncertainty occurs. Differences are calculated between the objective values of different plans, which give the level of regret between the plans and helps the planner's decision-making process. If the regret is zero for a future, it means that plan is optimal for that future. The measure of regret between plans is known as the risk and can be evaluated as (De la Torre, et al., 1999):

$$a_{i,j} = f(p_i, f_j) \tag{2.21}$$

$$a_{optimal,j} = f(p_{optimal}, f_j) \tag{2.22}$$

$$r_{i,j} = a_{i,j} - a_{optimal,j} \tag{2.23}$$

where in future f_j, $a_{i,j}$ is the objective value of plan p_i, $a_{optimal,j}$ is the objective value of the optimal plan $p_{optimal}$ obtained from an optimisation solution of the planning problem and $r_{i,j}$ is the regret. If no regrets are obtained for all future uncertainties analysed for a plan, it signifies the plan is robust. To make the "best decision", plan selection is achieved by setting different criteria in the treatment of the regret by the planner, including minimax regret criterion and expected cost.

2.3 Basic Concepts of Electricity Demand

Demand forecasting is a crucial aspect of power systems planning therefore some basic concepts of electricity demand are provided in this section. The definitions below refer to group *N* made of *n* customers.

1. Non-Simultaneous Peak Demand *(NPD)*: This is also referred to as the maximum diversified demand, which can be defined as the sum of the individual maximum demand pd_n of each customer within the group, and expressed as:

$$NPD = \sum_{n=1}^{N} \max(pd_n) \quad (2.24)$$

   There is a low probability of this occurrence on a power system due to differences in electrical energy consumption patterns across customers.

2. Simultaneous Peak Demand *(SPD)*: This is the group maximum demand observed over a given period *T* (hrs), expressed as:

$$SPD_{max} = max \sum_{t=1}^{T} \sum_{n=1}^{N} pd_{n,t} \quad (2.25)$$

3. Diversity Factor *(df)*: This is the measure of variance in the occurrence of individual maximum demand across the group, calculated as:

$$df = \frac{NPD}{SPD} \quad (2.26)$$

   This value is always greater than 1.

4. Load Factor *(LF)*: This is the ratio of the average simultaneous peak demand to the maximum simultaneous peak demand and can be calculated using:

$$LF = \frac{SPD_{average}}{SPD_{max}} \quad (2.27)$$

For the energy supplier, this is an indication of capacity utilisation since network equipment is provided to supply peak demand. High LF values indicate higher equipment utilisation since the average demand is close to the peak demand. Low LF values indicate underutilisation as peak demand exceeds average demand.

5. Load Duration Curve *(LDC)*: The load duration curve is a plot of demand in descending order to determine what percentage of time demand is above a certain level. Figure 2-11 shows a daily load profile and its load duration curve. The three load categories are the base load which occurs all the time, the peak load which occurs during the periods of maximum demand and the intermediate load which occurs between the peak and base load. A description of the mode of operation and cost analysis of generators for each load category is provided in section 2.2.3.

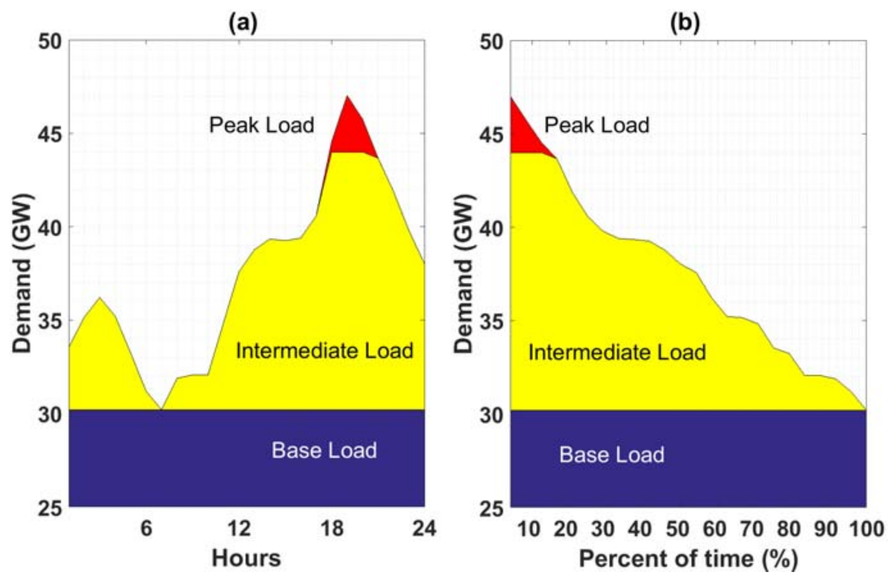


Figure 2-11: Load Curves (a) Daily Load Profile (b) Load Duration Curve

The area under both curves represents the electrical energy consumption E (Wh) of Power P (W) over time T (hours) and can be obtained using:

$$E = \int_0^T P(t)\ dt \tag{2.28}$$

6. Load Shedding: The managed disconnection of power supply to customers during periods of critical system conditions, e.g., generation shortages, to maintain network integrity is known as load shedding. This action suppresses the demand to the level of available power supply. This is different from demand side management where customers agree to interruption in power supply for a pre-arranged benefit with the supplier (Strbac, 2008). For load shedding, while customers may be warned before the interruption of supply 'blackouts', their consent is not required for it to occur (Kohler, 2014). During periods of load shedding, the network operator will aim to minimise the potential revenue losses by prioritising more profitable customers for load allocation (Xu & Girgis, 2001).

2.4 Demand Forecasting Techniques

The act of predicting future unknown values and events is known as forecasting. Forecasting is a valuable tool in planning, as it ensures risk analysis by considering various future outcomes in a bid to reduce or eliminate loss or unwanted results. (Wood, et al., 2014). Effective system planning requires accurately quantifying the locational demand to provide the requisite electrical network component along the power transmission value chain to deliver electricity, as the aim of power utilities is to efficiently supply demand. Demand forecasting is vital to power utility operations including unit commitment and load dispatch, spinning reserve management and maintenance scheduling.

Network capacity expansion requires reliable forecasts due to the costs involved with underestimating or overestimating demand. If capacity expansion is linked to underestimated demand, inadequate network capacity creates an unreliable and insecure system, symptoms of which include load shedding, network stabilisation inefficiencies, and insufficient reserve margins. Power shortages may lead to customers investing in alternative power sources at significant costs. For various sectors of the economy load shedding and rolling blackouts lead to under productivity, increased cost of operations and longer production times. The sudden interruption of power can also lead to health and safety hazards. The economy itself suffers as businesses pay less in taxes due to the erosion of earnings from power production costs and discourages new investment. While ‘overbuilt’ systems are more secure and reliable, they come at a significant cost ultimately borne by customers.

Electrical demand forecasting can be classified into short term, medium term and long-term forecasting. Short-term forecasts involve demand data of typically an hour to a few weeks and are influenced by diurnal weather patterns, weekday type and features such as the demand during a popular television program. This data is important for daily system operations and planning in the management of generation scheduling, maintenance, system security analysis and real-time network control. Medium-term forecasting typically ranges from a few weeks to a few years and involves demand assessment for maintenance scheduling, fuel inventory management and network reinforcements. Long-term forecasts include demand analysis over a long-time frame from one to thirty years (Al-Saba & El-Amin, 1999). Forecasts over this long duration are typically for capital investment and budgeting for generation and transmission network expansion to meet demand growth over the same period.

Forecasting techniques including time series, econometric and end use techniques are discussed in the following sections.

2.4.1 Time Series Techniques

These techniques relate to the establishment of relationships between the demand at various time intervals to predict future values. Examples of key time intervals that are important to planners are described below.

- Seasonal: This relates to changes in demand in response to changing weather conditions, for example, increased use of air conditioners (AC) during the summer months;
- Cyclical: This relates to demand variations, which occur over a period of years due to changes in underlying economic conditions, for example, impact of boom and bust cycles of crude oil prices on electricity demand;

- Trend: Consistent annual variations in demand irrespective of weather or economic impact.

While time series techniques can be used for short to medium term forecasting due to simplicity of execution and data requirements, this technique doesn't explain causality. Technological and economic changes that have a significant effect on energy use patterns cannot be accurately predicted using this method, for example, the increasing penetration of solar PV in homes reducing on-grid demand and the impact of recession on disposable income restricting the purchase of electrical appliances. (Gonzalez-Romera, et al., 2006), (Amarawickrama & Hunt, 2008), and (Kumar & Jain, 2010) have used time series forecasting for demand projections. Key examples are as follows.

1. Auto-Regressive (AR)

   In this method, past values of a variable are expressed as a linear regression to predict its future value. An AR model can be expressed in the form (Akaike, 1969):

$$X_n = \sum_{p=1}^{P} a_p \, X_{(n-p)} + \eta_{(n)} \tag{2.29}$$

   where $X_{(n-p)}$ are the historical demand values, a_p are the AR parameters and $\eta_{(n)}$ is the error term or white noise series. The model is described as an AR (p) model, for all p historical values of X_n used in the model. Time shifting, which allows X_n to be expressed in terms of its own historical values is achieved by using a backward shift operator B that can be used to define the historical value at time p using $X_{n-p} = B^p X_n$.

2. Moving Average (MA)

   In the MA method, the present value of the variable is expressed as a relationship with error terms (white noise series) of the time series. The error terms are constructed from the forecast errors from actual demand observations. The MA can be expressed in the form (Wood, et al., 2014):

$$X_n = \eta_{(n)} - \sum_{q=1}^{Q} \theta_q \, \eta_{(n-q)} \tag{2.30}$$

   where θ_q are the finite set of moving average coefficients at the observation time. The model is described as an MA (q) model in the order of q.

3. Auto-Regressive Moving Average (ARMA): Box–Jenkins

A combination of both the Auto-Regressive and Moving Average methods produces a broader and more complex model. It can be expressed in the form (Box, et al., 1994)

$$X_n = \sum_{p=1}^{P} a_p \, X_{(n-p)} + \varepsilon_{(n)} - \sum_{q=1}^{Q} \theta_q \, \eta_{(n-q)} \tag{2.31}$$

4. Auto-Regressive Integrated Moving Average (ARIMA): Box–Jenkins

The AR, MA and ARMA methods described above are applicable to time series described as a stationary process, whereby the means and covariance of variable observations are static over time. Electrical demand however, does not exhibit static behaviour. To analyse non-stationary time series variables, a differencing process achieves a transformation to a static time series. Differencing is the computation of change between two successive observations in a time series, and denoted by the operator ∇ expressed in B, the backward shift operator. A differenced time series of the order of one can be expressed in the form (Wood, et al., 2014)

$$\nabla X_n = X_n - X_{n-1} = (1 - B)X_n \tag{2.32}$$

For higher orders of differencing, it can be expressed as

$$\nabla^d X_n = (1 - B)^d X_n \tag{2.33}$$

The differenced model can then be analysed using the AR, MA or ARMA methods. For time series with p and q orders for the AR and MA parts, and a differenced order of d for the non-stationary transformation part, the ARIMA (*p, q, d*) model can be expressed in the form (Box, et al., 1994)

$$\varphi(B)\nabla^d X_n = \theta(B)\eta_n \tag{2.34}$$

where $\varphi(B)$ is the non-stationary autoregressive operator. AR models are used to generate the white noise series, which are then checked to determine their stationary state. Differencing is then applied to the series to correct for seasonality. With the controlled stationary error terms, the ARIMA model is then applied.

2.4.2 Econometric Techniques

These seek to establish a relationship between a dependent variable and factors that influence the historical performance of that variable. Upon establishing that relationship, the forecasted value of the variable is dependent on the real or projected values of the influencing factors. While trend analysis in time series forecasting projects future values of the variables if exogenous factors in future will remain largely constant, econometric forecasting seeks to determine causality (Raghavendra & Jyoti, 1996). For demand forecasting, this technique is used to project energy consumption patterns by establishing the influence of economic and technological factors on demand. Economic factors which have been used to forecast energy demand include GDP, population and energy intensity (Mirasgedis, et al., 2007), fuel prices (Duangjai, et al., 1996), energy price and income (Haasa & Schipperb, 1998), household welfare (Lam, 1998) and Industrial output (Christodoulakisa, et al., 2000). An econometric model can typically be expressed linearly in the form (IAEA, 1984):

$$Y_t = a + \sum b\,X_t \tag{2.35}$$

where b is the coefficient of the independent variable, X_t is the independent variable under investigation and a is the intercept.

2.4.3 Regression Techniques

This is one of the more common techniques used for forecasting due to its ease of implementation. It can be used to model the relationship between energy demand and other factors such as temperature and other weather conditions. Examples of such analysis include multiple linear regression (MLR) and polynomial regression. In other cases, the parameters are unknown and the regression function of the dependent variable is obtained by fitting a simple model at various target points, which are observations closest to the predetermined query points of the original data, this method is known as kernel smoothing (Hart, 1991).

The regression method aims to divide demand into a standard pattern and based on a linear relationship with independent variables (Singh, 2013). It uses the method of least-squares estimation. Regression can be expressed in the form (Singh, 2013):

$$Y_t = Y_{0,t} + \sum b_i X_{i,t} + \eta \tag{2.36}$$

where Y_0 is the standard demand at time t, b_i is the coefficient of the regression parameter, $X_{i,t}$ is the independent variable at time t, and η is the error term. MLR is a method used to project demand by modelling a linear relationship between a dependent variable and multiple independent variables. It can be expressed in the form (Singh, 2013):

$$Y_t = a_t Z_t + \eta_t \tag{2.37}$$

where Z_t is the vector of independent variables at time t, and a_t is the coefficient of the regression parameter.

2.4.4 Computational Intelligence Techniques

Techniques such as Genetic Algorithms, Fuzzy Logic and Artificial Neural Networks (ANN) have been developed to deal with the uncertainty associated with demand forecasting by using processes that mirror the performance of biological processes such as learning and genetics, to produce more accurate forecasts.

Genetic Algorithms are an approach that parallels the natural evolution process where the strongest of species survives in the selection of the optimal variable. It is a search technique involving an initial search point, a fitness function that evaluates the search points and stochastically controlled genetic operators that generate new search points (Ma, et al., 1995). An initial population of parent vectors (search points) is randomly generated. A mating pool of parent vectors is selected from the group by using the fitness function to test those with best-fit values that have a chance of survival in the subsequent generation. Selected parent vectors then produce offspring either through crossover, i.e., merging or by mutation, i.e., modification of offspring. This same is repeated until the maximum number of generations has been achieved or fitness cannot be improved any further. Genetic Algorithms have been used for long-term forecasting (Lee, et al., 1997), short-term forecasting (Tzafestas & Tzafestas, 2001), monthly energy consumption (Azadeh & Tarverdian, 2007), fuel demand forecasts (Ozturk, et al., 2004), sectorial energy consumption analysis (Forouzanfar, et al., 2010) and total country energy demand modelling (Ceylan & Ozturk, 2004).

Fuzzy Logic is an approach that parallels the degree of truth inference in the human decision-making process. Unlike Boolean rules that set values to 1 and 0, fuzzy rules determine a value based on a degree of comparison, allowing values to be selected within a boundary range. A membership function defines the values of input variables, by mapping each element of all input sets to a value between selected ranges (Zadeh, 1965):

$$Y = \{x, \mu_Y(x) | \, x \in X\} \tag{2.38}$$

where μ_Y (x) is the membership function of x in *Y*. It assigns values to all elements of *X*. Logical operators and conditional statements are then used to define output sets, which are "defuzzied", assigning a value to the output. An If statement precedes the logical operation among values as expressed below

$$\mu_{Y \cap Z \cap Q}(x) = B(\mu_Y(x), \mu_Z(x), \mu_Q(x)) \tag{2.39}$$

where B represents a binary operator aggregating the input values. The resulting value is then subject to a conditional rule, which sets the output value.

Fuzzy logic has been used for peak load forecasting (Kiartzis, et al., 2000), spatial forecasting (Miranda & Monteiro, 2000) and short-term load forecasting (Mamlook, et al., 2009) & (Chaturvedi, et al., 2015).

ANN models parallel the neuronal activities of the brain, which is a system of interconnected processing elements called neurons. A non-linear transfer function process occurs at a node on the combination of signals received from other nodes in a previous layer. This node produces an output signal, which in the next layer, serves as an input signal for other nodes. The total signal network activity creates an efficient computational process. Multi-layer perceptron (MLP), one of the more typical ANN models, are made up of several layers of neurons. The first layer, which receives the information to the network, is the input layer. The final or output layer is where the network solution is contained, and in between, is the hidden layer. Arcs from a lower to higher layer connect each node in a neighbouring layer.

A simple mathematical representation can be presented as (Warner & Misra, 1996):

$$y_i = \Theta\left(\sum_j w_{ij}\, x_j - \eta_i\right) \tag{2.40}$$

where y_i is the output of neuron i, w_{ij} is the weight from neuron j to neuron i, x_j is output of neuron j, η_i is the threshold for neuron i, and Θ is the activation function, defined as,

$$\Theta(\text{net input}) = \begin{cases} 1, & if \text{ net input} \geq 0 \\ 0, & otherwise \end{cases} \tag{2.41}$$

where *net input* is the weighted sum of inputs to the neuron from the connected units. ANN models emulate nonlinear regression models when used for explanatory forecasting given a set of independent variables to predict a dependent variable. In time series forecasting however, they emulate nonlinear autoregressive models, as the input variables are historical observations while outputs are future values (Zhang, et al., 1998). ANN models are trained to perform tasks by determining the arc weights of node interconnectors. Information is stored in each arc in the form of arc weights, enabling signal mapping between input and output nodes. Arc weights that minimise error measures are typically the objective of model training. ANN models have been used for long term demand forecasting (Ekonomou, 2010), (Kankal, et al., 2011), (Kandananond, 2011) and (Panklib, et al., 2015). They have also been used for short term load forecasting (Park, et al., 1991), (Darbellay & Slama, 2000), (Yalcinoz & Eminoglu, 2005), and (Hernández, et al., 2014).

2.4.5 End Use Techniques

Energy forecasting with end use techniques requires detailed analysis on final energy use. Such models identify the energy demand of end users, estimate total energy consumption over a period and then aggregate demand for the end users. A simple mathematical presentation for end use demand is in the form (Broehl, 1981)

$$D_{ij} = N_i C_i F_{ij} \tag{2.42}$$

where D_{ij} is the demand at hour j by end use component i, N_i is the number of end use components of type i, C_i is the connected load per use component of type i, and F_{ij} is the fraction of the connected load of use component i which is operated at hour j.

Energy consumption E_i is the aggregate demand of all end use demands over period j as in:

$$E_i = \sum_j D_{ij} \tag{2.43}$$

End use forecasting has been used for different classes of end use size including energy consumption by buildings (Ashouri, et al., 2013), heating energy demand for a city (Strazalka, et al., 2011), and sectorial energy use in a country (Medlock III & Soligo, 2001). End use modelling approaches can broadly be categorised into 2 methods, top-down and bottom-up (Zhou & Lin, 2008). The top-down method integrates econometric and technological data in its forecast modelling. It seeks to determine the changes in energy consumption patterns in response to changes of key economic variables such as GDP, population, energy prices, electrical equipment ownership and energy efficiency targets. Zhang (2004), Canyurt et al (2005) and the residential demand estimates in the US national energy model (U.S Energy Information Administration, 2017) have used this approach in forecasting energy use. Bottom-up modelling aims to determine the contribution at end use to total energy demand. Bottom-up modelling can generally be categorised into two methods: statistical and engineering (Swan & Ugursal, 2009). Statistical approaches apply similar datasets used in the top-down approach, and then apply methods such as regression and neural network analysis to determine end use demand. Engineering approaches aim to model energy use based on the power rating of the end-use electrical equipment. This can be achieved through 3 methods (Swan & Ugursal, 2009)

1) Distribution: This method is based on electrical appliance ownership data at the end use level and aggregates the total energy consumption per appliance. This has been employed by Capasso, et al., (1994); LaCommare, et al., (2002), Yao and Steemers, (2005); Richardson, et al., (2010); and Collin, et al. (2014).
2) Archetypes: This method is based on the building stock distribution at the end use level, and aggregates energy consumption per building stock type has been used by Shorrock and Dunster (1997); Deru, et al. (2011); Hostick, et al., (2012) and Merkel, et al., (2013).
3) Sampling: This method is based on survey results of energy consumption at the end use level. Results can then be extrapolated for larger sets of end users

to predict total energy use Larsen and Nesbakken, (2004); and Thomas, et al. (2010).

2.4.5.1 After Diversity Maximum Demand

In Low Voltage (LV) network system planning, the estimation of the rating of network power equipment to be placed in a location is based on a standard method known as the After Diversity Maximum Demand (ADMD). The ADMD is the maximum simultaneous demand per customer on a node of that network. The observed maximum demand is usually obtained by monitoring customers with similar energy usage attributes over a period of a year. Typically, aggregation is limited to 1000 customers as there is no significant change in the diversity factor beyond this population. The ADMD (kVA) and diversity can be represented below using (McQueen, et al., 2004) and (Kersting, 2012)

$$ADMD = \lim_{J \to \infty} \frac{1}{J} \sum_{j=1}^{J} MD_j \tag{2.44}$$

where *ADMD* is the after diversity maximum demand per customer within a group of customers *J*, MD_j is the demand of customer *j* at the period of maximum simultaneous demand. The maximum demand can then be obtained using (Boait, et al., 2015).

$$MD_{simultaneous} = (ADMD \times N) + k \tag{2.45}$$

where *N* is the total number of customers and *k* is an empirically determined factor based on a customer population. Scottish and Southern Energy (2003) used a *k* value of 18kW for each branch in the network from the substation to the farthest network point. The value of *k* can also be used to represent the power rating of the largest appliance among that customer group.

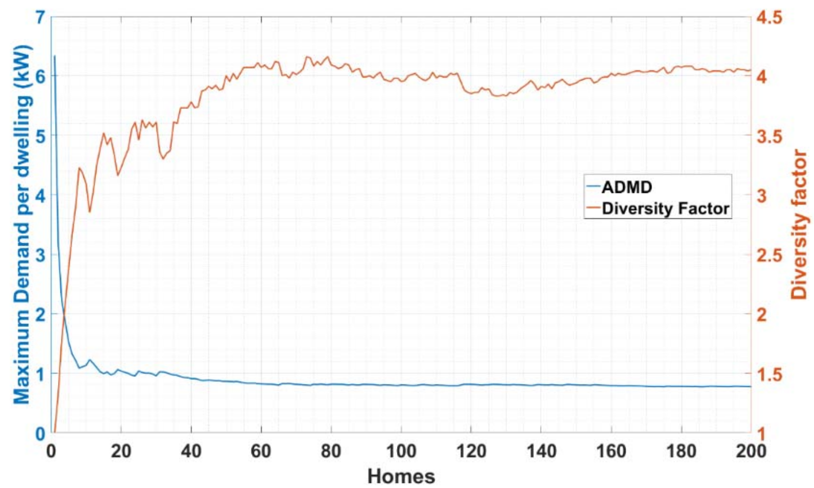


Figure 2-12: ADMD and Diversity factor for 200 homes

Figure 2-12 shows the ADMD and diversity factor simulation for 200 homes. High variability is noticed in both plots when the number of households is less than 40. The impact of the individual peak demand contribution of a household to the overall peak demand as a ratio to the total number of households attenuates as the number of households increase. The ADMD stabilizes at 0.8kW, which is the expected contribution of the *nth* home to the peak simultaneous demand. The diversity factor, which is a measure of the variance of individual household peak demand, has a value of 4.05.

<u>Methods of ADMD estimation</u>

ADMD estimation methods as defined by the Council for Scientific and Industrial Research (2000) are presented below:

1) Appliance modelling: This is used to estimate the electricity demand contribution and energy consumption of each appliance to the household demand. This method requires knowledge of appliance saturation in study and details of household behavioural patterns for modelling household electricity use.
2) Direct Measurement: This method requires peak demand measurement at the transformer level in a study area that supplies the same customer class of electricity consumers.

3) Energy load factor: This method is applied using energy sales data and estimating the peak demand with an assumed load factor for each customer class to be evaluated.

The maximum simultaneous peak demand for a group of customers is dependent on the income level of that group which influences electrical appliance ownership. Customers with higher income levels can afford more appliances with higher power ratings e.g. saunas or hot tubs, than lower income level customers. Behavioural patterns across a group of customers influence lifestyle habits that drive electrical power use. The morning pick-up load noticed in typical residential load curves is influenced by the wake-up period of households under the curve and use of electrical appliances after waking up e.g. taking a shower or switching on the kettle. Special events such as public holidays or watching of a popular television programme among customers in a location can also drive the total electrical demand in that location.

Maximum demand is also influenced by weather in a location (Trotter, et al., 2016). For areas with high AC appliance ownership, the cooling demand will be driven by the severity of warmer temperatures. For this appliance type and similar electric motor driven appliances, the impact of current transients when the appliance is activated also impacts the maximum demand (Gordon, 2009). Network equipment such as transformers are vulnerable to such load pick up particularly in areas affected by intermittent power supply. Upon power restoration, the probability of appliance activation across customers in that location is high leading to possible voltage drops and equipment failure. The network voltage quality also affects the demand of customers supplied, as lower voltage levels may reduce demand.

The ADMD method has been used globally in forecasting LV and residential demand with application in UK, (UK Power Networks, 2014), (Scottish Power Energy Networks, 2013), (Scottish and Southern Energy, 2003); Australia, (Horizon Power, 2013), (Ausgrid, 2015); and South Africa (ESKOM, 2003) (Council for Scientific and Industrial Research, 2000). Elexon, responsible for the electricity market balance and settlement in the UK, uses the group average demand and energy consumption of customers within categorised domestic customer profiles for the UK, for its annual energy consumption analysis and estimation (ELEXON, 2013).

Customers in the same income group typically exhibit similar electricity consumption patterns and the classification for South African customers provided by ESKOM (2003) is presented in Table 2-4.

Table 2-4: ADMD Customer Consumption Class

Consumption Class	ADMD kVA	~Annual Energy MWh/Yr.	~ Monthly Energy kWh
Very High	6 - 9	> 19	> 1600
High	3 - 6	7.5 – 19	600 – 1600
Medium	1.5 - 3	3 – 7.5	250 – 600
Low	0.5 – 1.5	1.2 – 3	100 – 250
Very Low	≤ 0.5	< 1.2	< 100

i. Very Low: Electrical appliance use in this category is typically for lighting and entertainment e.g. radio and television

ii. Low: Electrical appliance use in this category is typically limited to lighting, entertainment, refrigeration and could also include ironing.

iii. Medium: Electrical appliance use in this category is includes those listed in the Low category along with cooking and air conditioning.

iv. High: Electrical appliance use in this category includes those listed above, along with water heating, laundry and increased air conditioning.

v. Very High: Electrical appliance use here would include additional usage of appliances used in the High category.

2.4.6 Comparison of Forecasting Techniques

Different techniques have been discussed above, each with their advantages and drawbacks. Suitability of each technique for forecasting is dependent on availability of data, significance of causality, functionality, simplicity versus accuracy requirements and computational resources.

While time series models are simple in implementation, structural changes of key parameters in historical data might not be predicted accurately in future projections. If not treated in the analysis, effects such as the climate change impact on weather variables that affect electricity demand might be understated and lead to inaccurate projections.

Regression and econometric models rely on historical statistical estimates of independent variables for accurate projections of demand. For developing countries, availability of the required statistical data for demand studies might prove to be a challenge. While non-parametric regression can be applied to forecasts, they are complex and will produce fits that emulate unexplained trends in the original observations. In countries where demand far exceeds generation e.g., Nigeria, demand is typically a function of available generation capacity. Forecasting studies in a country with historical shortages in power supply based on its on-grid energy distribution can be misleading if off-grid energy consumption is not captured (Akinlo, 2009). While positive relationship trends might be deduced between economic variables and energy consumption, projections might underestimate future energy demand if supressed demand is not treated in the analysis.

Adaptability and nonlinearity of computational intelligence models such as ANN are some of the strengths of such models. However, they require large data sets and expert input for training the model. Transfer function mapping between nodes involves trial and error attempts. They are also described as black-box methods as they do not provide insight into causality (Zhang, et al., 1998).

End use model projections give insight into energy use at the consumer level and detailed forecasts on overall energy consumption. However top-down approaches, which are more suitable for energy supply side analysis, might fail to capture the impact of technological influences at the end use level and overestimate demand (Haasa & Schipperb, 1998). Bottom-up approaches are significantly dependent on end user occupant behaviour (Ndiaye & Gabriel, 2011) and may fail to predict changes in consumption pattern that impact energy consumption. End use models need regular updates of underlying assumptions of model parameters.

2.5 Weather and Electrical Demand

Figure 2-13 shows the seasonal hourly electrical demand profile for the UK. There are typical demand patterns shown below for each season, influenced by the prevailing weather conditions. The maximum demand profile is observed in winter due to increased electrical demand for space heating, while summer sees the lowest demand profile as the demand for space heating diminishes due to warmer external temperatures.

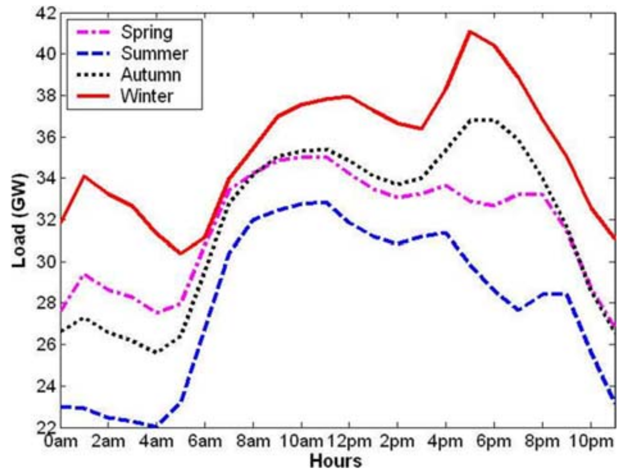


Figure 2-13: UK seasonal electricity demand profiles (Hor, et al., 2005)

As temperatures get warmer, the electrical demand from appliances such as ACs for space cooling, and refrigerators for cold drinks, increases. Colder temperatures see an increase in the electrical demand from space and water heaters. The seasonal influence of weather on electricity demand is location dependent as climatic conditions vary across the world (Isaac & van Vuuren, 2009) (Li, et al., 2012). Another aspect to this influence is also determined by the socioeconomic conditions of the location to be analysed, which determines the saturation of weather related appliances among energy end users (Sailor & Pavlova, 2003). Due to this sensitivity, demand forecasting models often include a weather component.

The temperature threshold at which thermal conditions become uncomfortable and cause changes in electricity demand in response to the discomfort is the balance point temperature. Figure 2-14 shows the theoretical relationship between temperature and energy consumption. The balance point temperature is the point at which demand is unresponsive to temperature and gives the non-weather sensitive energy consumption. Changes in temperature below and above the balance point sees a response in energy consumption. In demand forecasting, the typical temperature thresholds used to establish this balance point and weather component are the cooling degree days (CDD) for warm temperatures, and heating degree days (HDD) for colder temperatures. The degree days are a measure of variance between daily temperatures and a threshold temperature. For CDD, it is a measure of variance above the threshold, while for HDD, it is a measure of variance below the threshold.

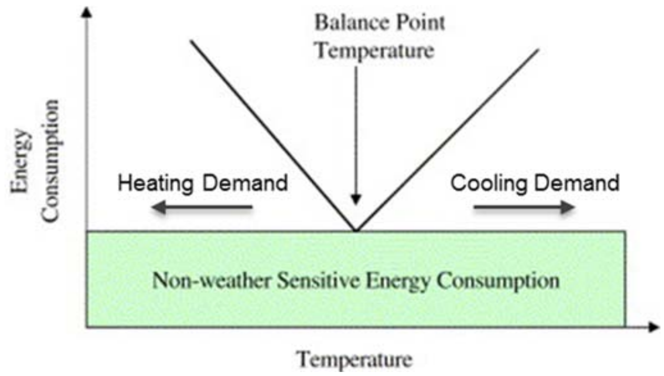


Figure 2-14: Relationship between temperature and energy consumption (Jager, 1983)

The CDD and HDD for days *D* can be evaluated using:

$$CDD = \begin{cases} \sum_{d=1}^{D} (T_d - T_b) \; for \; T \geq T_b \\ 0 \qquad\qquad\qquad otherwise \end{cases} \tag{2.46}$$

$$HDD = \begin{cases} \sum_{d=1}^{D} (T_b - T_d) \; for \; T \leq T_b \\ 0 \qquad\qquad\qquad otherwise \end{cases} \tag{2.47}$$

where T_d is the daily external temperature (°C), T_b is the threshold temperature (°C). The degree days vary with climatic conditions globally (Isaac & van Vuuren, 2009).

The sensitivity of electricity demand to weather can then be assessed using a simple linear regression analysis:

$$W_D = A_0 + A_1(CDD) + A_2(HDD) \tag{2.48}$$

where W_D is the daily demand (Wh), and A_0, A_1, A_2 represent the regression coefficients relating consumption to *CDD* and *HDD.*

It is possible to develop hourly equivalent models based on cooling degree hours and heating degree hours. This approach has been applied to various techniques used to forecast demand in the US (Ruth & Lin, 2006) (Perez-Lombard, et al., 2008) (Hong, et al., 2013), EU (Bessec & Fouquau, 2008) (van der Linden & Mittchell, 2009) (Moreci, et al., 2016), UK (Hor, et al., 2005) (Day, et al., 2009) (McGilligan, et al., 2011), and Asia (Parkpoom & Harrison, 2008) (Lee & Levermore, 2010).

In Africa, the inclusion of temperature in demand forecasting has been limited. In South Africa, Amusa, et al., (2009) and Inglesi (2010) both argue that industrial demand, the major driver of demand is independent of temperature, and hence do not include temperature in their national forecasts. This may also be as a result of unavailable temperature data (Ziramba, 2008). However, Chikobvu & Siguake (2013) establishes the influence of temperature on daily peak electricity demand in South Africa. In Namibia, Vita (2006) also showed the response of energy to temperature, with higher energy consumption with respect to lower temperatures due to its temperate climate. In Tunisia, Gam & Regeb (2012) have shown that a 1% increase in average temperature will increase electricity consumption by 1.32%.

2.6 Summary

This chapter has presented a discussion on power systems, along with typical system considerations for expansion planning. An introduction to electricity demand and a review of demand forecasting techniques have also been presented. The relationship between electricity demand and weather has also been assessed, along with a review of its adoption in global demand forecasting research. The following chapter presents a description of the Nigerian electricity market and establishes the focus of this research.

Chapter 3
Electricity Industry in Nigeria

The liberalisation of the Nigerian electricity industry in 2013 has seen its evolution from a government led monopoly to a liberalised electricity market, currently in a purchasing agency structure. The current market is beset with challenges along the value chain including: gas supply constraints, a limited transmission network infrastructure, and liquidity challenges due to tariff regulations at the distribution level.

While a long-term network expansion plan has been put in place by the government to bridge the power supply gap, in the short term, an understanding of the national electricity demand pattern is important to improve current inefficient load management and shedding programs. Long term expansion plans must be linked to scientific demand studies for optimality to prevent under-investment and over-investment in capacity.

This chapter presents an overview of the current electricity market, performance of the key sectors and the characteristics of demand in Nigeria.

3.1 Electricity Industry in Nigeria

The Nigerian Electricity Power Authority (NEPA) was created in 1972 from the union of Electricity Corporation of Nigeria and the Nigerian Dam Authority with the sole mandate of regulating and maintaining electricity supply in Nigeria (Ohajianya, et al., 2014).

The 2005 Electric Power Sector Reform Act (EPSRA) saw the transformation of NEPA to the Power Holding Company of Nigeria (PHCN), with the new entity assuming all the assets, liabilities and human capital of NEPA. The Act aimed to ensure the eventual unbundling of PHCN into 18 successor companies and the establishment of the National Electricity Regulation Council (NERC). Electricity supply by PHCN was marred by outages and inefficient power supply which could be attributed to the gap between installed nameplate capacity 12.4GW and the constrained peak generation capacity of 4.5GW for a population of over 160 million people. The establishment of the Power Sector Roadmap in 2010, saw the successful unbundling of PHCN into six generation companies, eleven distribution companies and the transmission company, with the government still in discussions with prequalified bidders for ten National Independent Power plants (NIPP). This development also saw the Transmission Company of Nigeria (TCN), retained by the government, entering into a technical management agreement with a power consulting firm.

3.1.1 Overview of selected market participants.

1) Nigerian Electricity Regulatory Commission: NERC, the independent regulatory agency was established to regulate and oversee the power sector. It roles include licensing power market participants, approval of market rules and regulation of market operations, approval of systems codes and standards, and promoting private sector participation.
2) Nigeria Bulk Electricity Trading Plc: NBET is the government owned wholesale electricity trading company that procures electrical power and ancillary power services from generation companies and sells to distribution companies and other large consumers.
3) Generating Companies: There are currently 25 grid connected generating power stations with a combined installed capacity of 12.4GW, and a current average operational capacity of 3.9GW. There are 12 other projects at various stages of completion with a combined capacity of 3.8GW. Installed Hydro generation capacity is 2GW while thermal generation capacity is 10.5GW. Generation companies in Nigeria fall into 3 categories: Independent Power Producers (IPP), National Integrated Power Projects (NIPP), and privatised generation companies (NESI, 2015).
4) Transmission Company of Nigeria: TCN is made up of two departments, the system operator and market operator.
    i. Operator of the Nigerian Electricity Market (ONEM): ONEM functions as the administrator of the wholesale market with responsibilities for

implementing market rules, managing market billing arrangements and centralising commercial metering data from market participants.

ii. Nigerian System Operator (NSO): The NSO functions to enforce the grid code, plan the system, undertake dispatch and generation scheduling and ensure reliability and availability of ancillary services. The transmission network consists of 159 substations with a wheeling capacity of 5GW with ongoing projects expected to increase the capacity to 13GW.

5) Distribution Companies: There are 11 Distribution Companies (DisCo) in Nigeria. The coverage area by DisCo is shown in Figure 3-1.

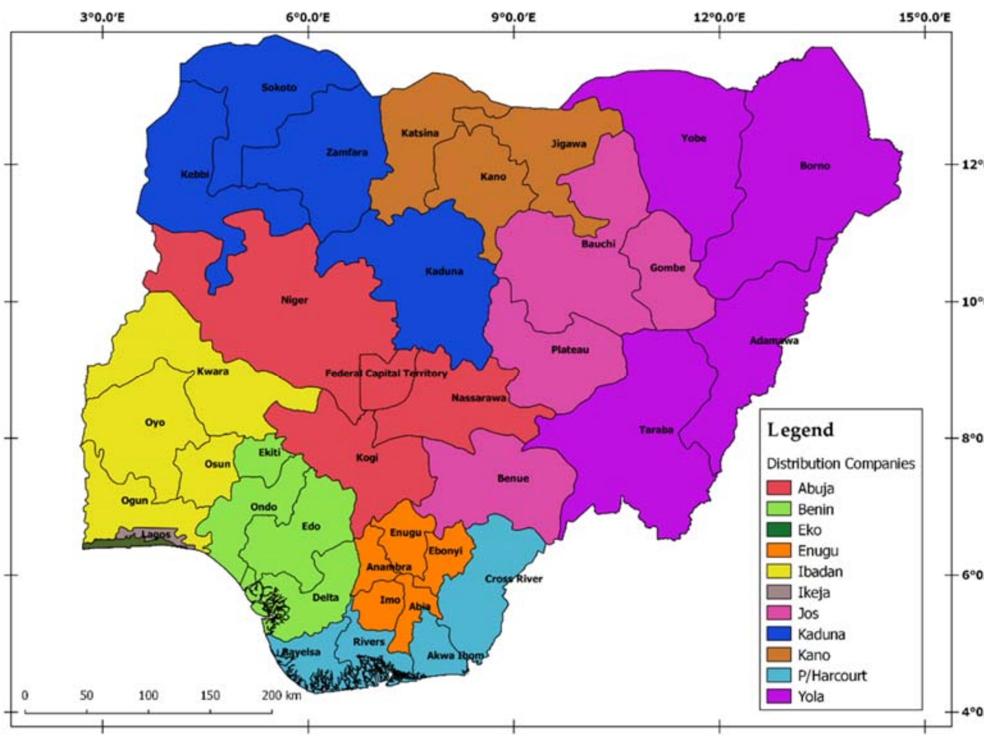


Figure 3-1 Map of Nigeria showing Distribution Companies

3.1.2 Nigeria Electricity Market

Commencing in February 2015, NERC initiated the Transitional Electricity Market (TEM) in Nigeria with contractual electricity trading among market participants. Power purchase agreements (PPA) are entered into between the power generating companies and the bulk purchaser, NBET, while vesting contracts are executed between NBET and the DisCos. The market framework is shown in Figure 3-2. The Transmission Use of System agreement is also executed between NERC and TCN. Other contracts such as the Gas Purchase agreements, Ancillary Services Agreement and Grid Connection Agreements are also executed between the respective electricity market service providers and NBET.

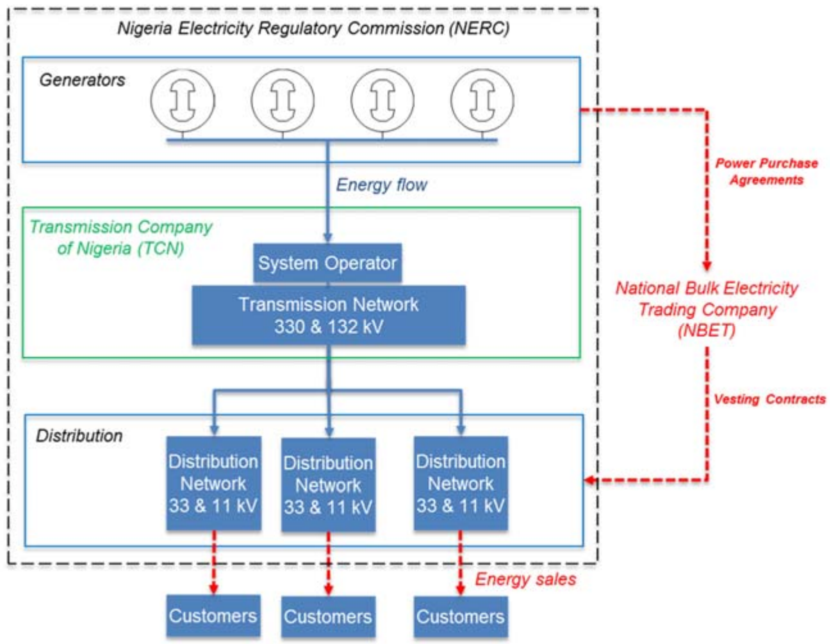


Figure 3-2 NBET Transitional market network

The system and market operators are responsible for implementing market rules and managing inadequate generation supply and shortages, while also performing the generation adequacy analysis and ensuring shortages are distributed equally among the distribution companies. Other responsibilities include the procurement of ancillary services, centralisation of commercial metering data, administration of the wholesale electricity market settlement and payment system, admission of market participants and maintenance of a market administration database.

The plan is for TEM to evolve into a medium-term market with competition among generation companies, a central balancing mechanism via a spot market, and bilateral energy trading between generation and distribution companies.

3.2 Power Supply in Nigeria

The available sources of energy in Nigeria include hydro, natural gas, coal, wind, solar and biomass. However, grid energy supply is characterised by hydro and thermal generation. With Nigeria's abundant gas reserves, the current thermal generation capacity is made up of 4 combined cycle gas stations, 2 gas fired steam stations and 17 open cycle gas stations. There are currently 3 hydro stations with plans in place to build 2 new stations. There are currently plans to convert some of the existing open cycle gas stations into combined cycle gas stations. The following sections provide an overview of the key segments of Nigeria's power supply.

3.2.1 Generation

The electrical power generation capacity of Nigeria witnessed rapid growth from the late 1970s as government revenues increased significantly as a result of the Organisation of the Petroleum Exporting Countries oil price increases. This oil wealth boom also impacted the living wage of Nigerians as the economy witnessed an expansion and the purchasing of household electrical appliances increased (Adegbulugbe, et al., 2007).

However, this rapid rate of increase in energy demand was not accompanied by a growth in power infrastructure investment, as government revenue largely dependent on crude oil exports, trended downwards as international oil prices slumped in the early 1980s (Budget Office of the Federation, 2016). The 1990s saw negligible investment in the power sector as Nigeria grappled with governance challenges in the form of military rule (Figure 3-3). The return to democratic rule in 1999 changed the government power sector policy as investment ramped up rapidly and the following decade witnessed a positive growth rate compared to the decade preceding 1999 (Figure 3-4).

2005 saw the beginning of the National Integrated Power Projects (NIPP) programme established by the Niger Delta Holding Company (NDPHC) as a government funded and led intervention scheme to increase power capacity with the construction of ten gas fired power plants as well as other transmission and distribution projects (Adegbulugbe, et al., 2007). Before the implementation of this programme, the total installed capacity owned by the government of Nigeria was 5.8GW with only 50% of that available. As at 2015, only eight of these NIPPs had been commissioned with a total installed capacity of 4.3GW.

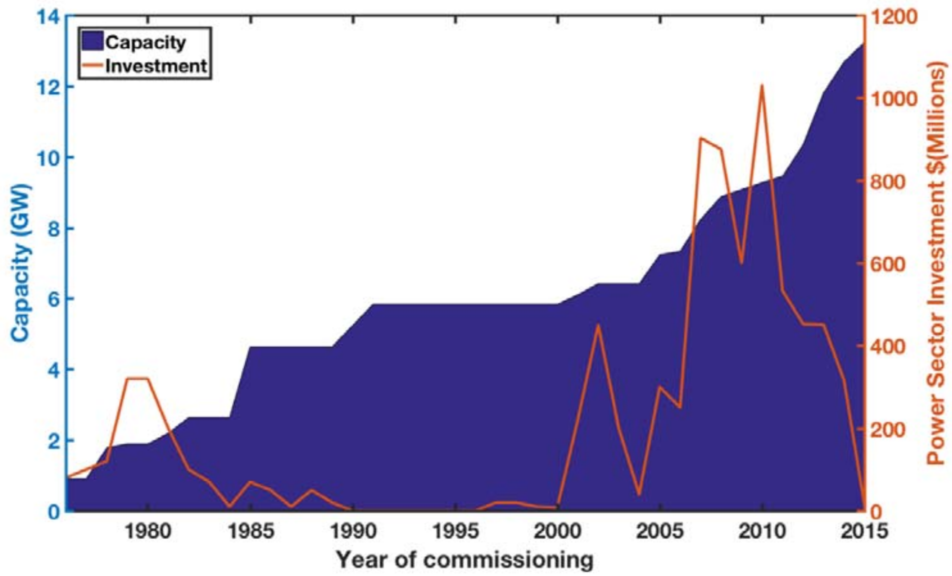


Figure 3-3 Generation Capacity vs Investment

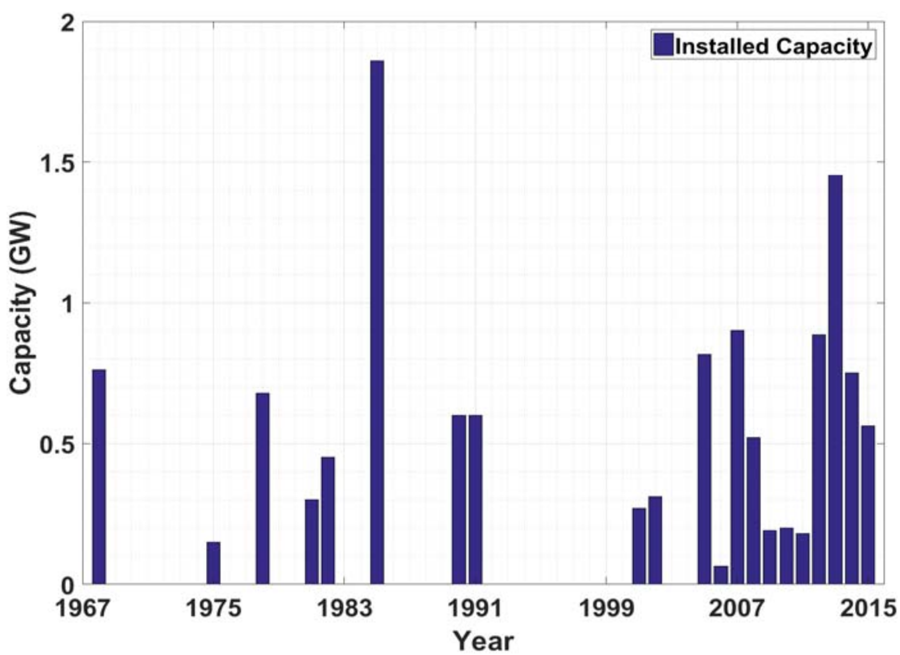


Figure 3-4: Historical generation capacity additions (TCN, 2017)

The 2005 Electric Power Sector Reform Act allowed for the participation of the private companies in the power sector, and five Independent Power Projects (IPP) were embarked upon to boost capacity. Two are state government led ventures while the other four are owned by private companies. The six IPPs are gas fired with totalled installed capacity of 1.9GW.

Subsequent infrastructure investment has seen the total installed capacity, shown by station type in Table 3-1, increased to 12.4 GW (NESI, 2017). The 2013 privatisation exercise saw the government divest its ownership stake in the power generation stations, with an outright sale of three thermal power stations and partial divestment in another two. The three hydro stations are under concession agreements. The NIPPs have been retained by NDPHC, although there are government plans for further divestments, these have been hampered by an inconclusive bidding exercise and a change of the country's leadership.

In the south of the country, the Niger Delta, with the 9th largest proven gas reserves in the world, is where most of the gas turbines are located (NESI, 2017) (see Figure 3-5). The hydro stations are located further north as dams on the river Niger. However, political unrest in the Niger Delta region beginning after the collapse of military rule has seen frequent damaging of gas pipelines, significantly constraining gas supply to power stations.

Table 3-1: Power generation capacity in Nigeria

Power station type	Capacity (GW)
CCGT	2.4
OCGT	6.3
Steam	1.8
Hydro	1.9
Total	12.4

Recent historical data shows poor capacity utilization of the power stations mainly due to gas shortages for the gas turbines and water level constraints for the hydro stations (NESI, 2015). High frequency and line loss constraints also contribute to the supply challenges as wheeling capacity of the transmission network is about 4.8GW compared to the average available generation capacity of 7GW. Average operational capacity as a percentage of installed capacity between 2013 and Sept 2016 is 32%. This trend is shown in Figure3-6. The constraints include gas supply (61%), transmission (17%), water (14%) and others (8%). Total energy generated for 2015 was 29.6TWh (2014 28.3TWh) (Nigeria Electricity System Operator, 2018).

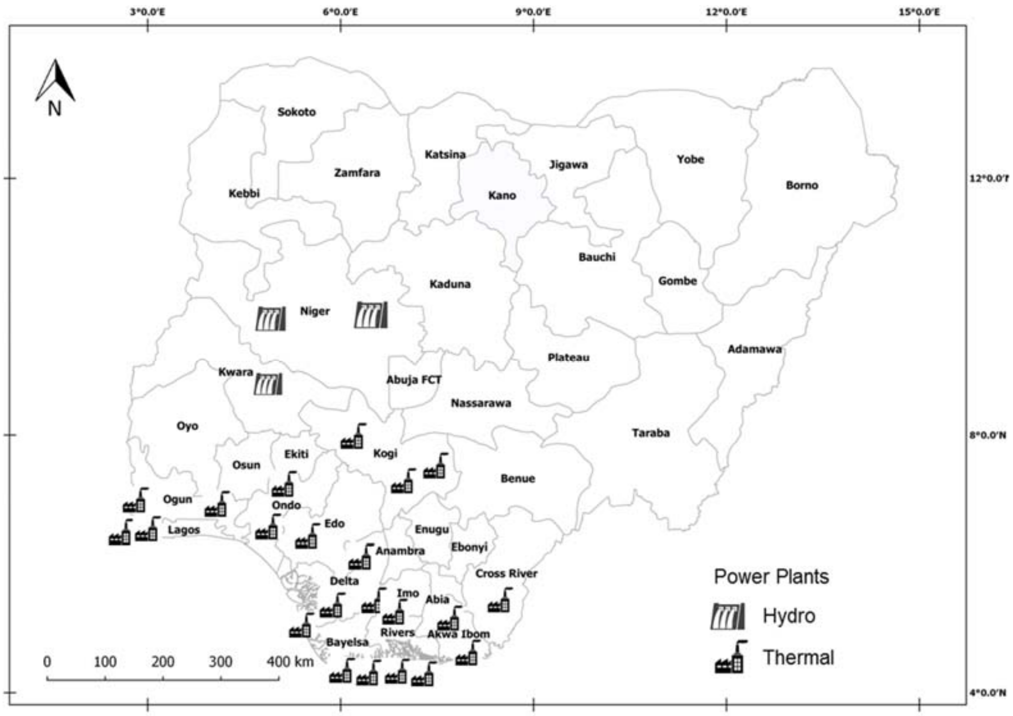


Figure 3-5: Nigeria power generation stations by location (TCN, 2017)

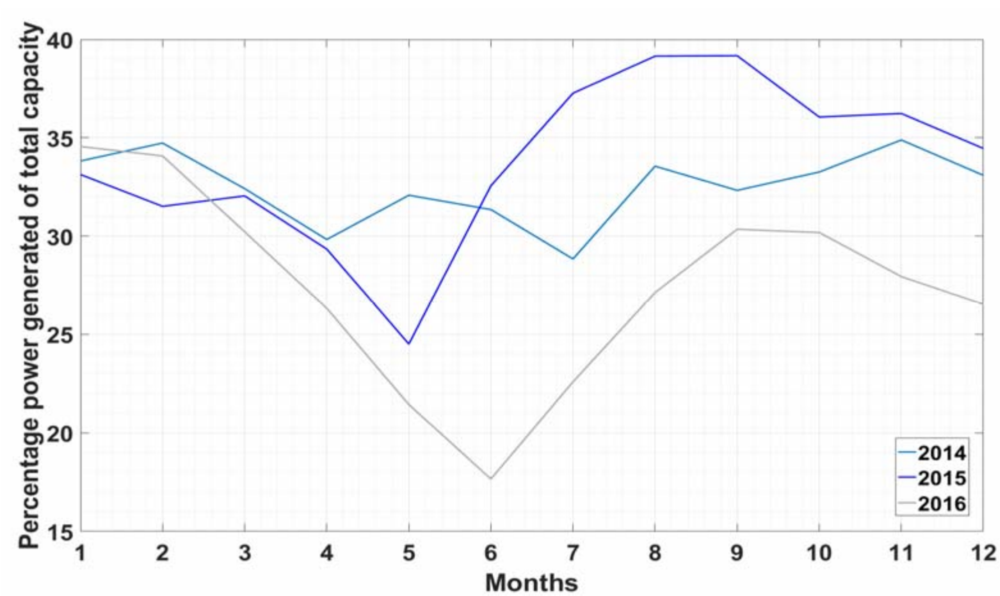


Figure3-6: Available Generation capacity trend (%) (TCN, 2017)

As part of its responsibilities to encourage private sector investment in the electricity market, NERC has issued over 75 power generation licenses to various investors (NERC, 2015). These licenses also include off-grid captive, islanded and embedded generation licenses to enable Discos and large consumers buy energy from off-grid generators to bridge the supply gap from the national grid.

Types of Generation licenses

i. On-Grid Licenses: Licenses for generators connected to the transmission network at the 330kV level. E.g. the NIPPs and successor Generating companies
ii. Off-Grid and Embedded Licenses: Licenses for large generators connected directly to the distribution networks at the 33kV level or which transmit power at 132kV level.
iii. Captive Generation consent: Regulatory consents for self-generation exceeding 1MW are required. The generators are able to sell power not exceeding 1MW to a power purchaser. Sales of exceeding 1MW require generation licenses.

Hydro generation accounts for 22% of total power generation, while thermal accounts for 78% which shows a lack of diversification in Nigeria's energy mix. This section looks at the types of generation available in Nigeria.

3.2.1.1 Hydro Generation

The hydro dams are located on the River Niger that has its source at Fouta Djallon in the Republic of Guinea. The rainy season in Guinea occurs between May and October, with its wettest months occurring in July and August (see Figure 3-7). This increases the water levels and urges a downstream flow over the following two months to the river Niger. Kainji and Shiroro dams experience their highest water inflows between June and September, while Jebba dam experiences its highest inflows between September and October. The average monthly power generated and reservoir inflow for the hydro stations between 2013 and 2015, are shown in Figure 3-8.The average annual inflow (2013-2015) for Kainji, Jebba and Shiroro are 1,127m^3/sec, 1,146m^3/sec and 293m^3/sec, with an annual average power generated of 110MW, 214MW and

190MW, respectively. Due to maintenance and water supply issues, the power generated over this period yielded a capacity factor of 14%, 37% and 32% for Kainji, Jebba and Shiroro respectively.

Coincidentally, these are the rainy season months in Nigeria and have led to a public theory that the rains in Nigeria increase energy generation. The government is also working on developing two new hydro projects, Zungeru 700MW and Mambilla Hydro 3.5GW.

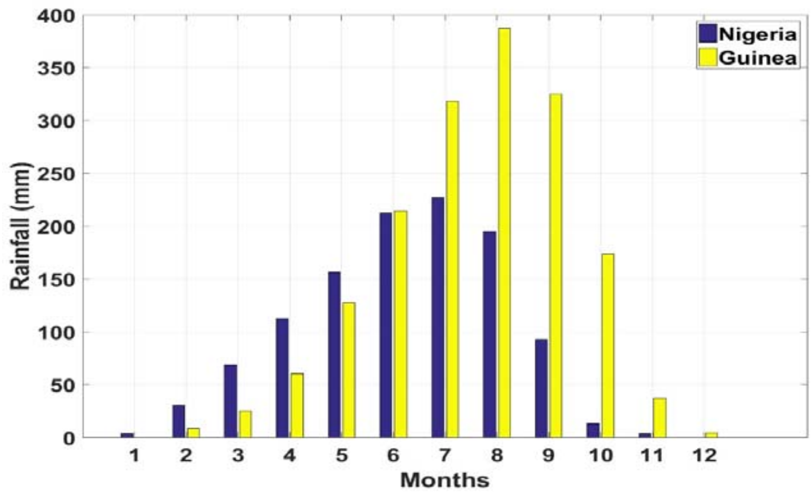


Figure 3-7 Annual Rainfall: Nigeria and the Republic of Guinea (United Nations, 2010)

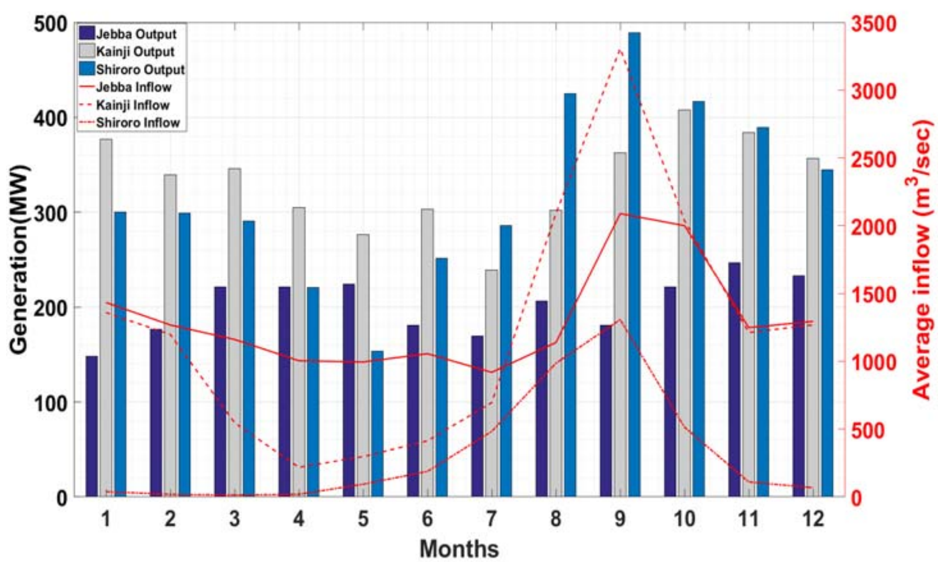


Figure 3-8 Annual Hydro Generation trend (TCN, 2017)

3.2.1.2 Thermal Generation

Despite having the 9th largest proven gas reserves in the world, gas supply still remains a challenge in Nigeria. The major reasons for this are the lack of adequate infrastructure and unresolved crisis in the Niger Delta region. Before the liberalisation of the electricity market, the government set gas prices and the pricing did not encourage investors to participate in the sector. As such, the gas pipeline projects which have been government led in partnerships with International Oil Companies (IOC) operating in the Niger Delta region, are not adequate to meet internal energy demand. In 2014, gas prices were reviewed and while pricing is not free floating, it was marked to the Henry Hub natural gas spot price average for 2014 (Platts, 2014). The gas price of \$2.5/MMBtu and transport cost of \$0.8/MMBtu is yet to spark the desired investment drive due to the other challenge, the Niger Delta crisis. Political unrests in the Niger Delta region has caused frequent damaging of gas pipelines, constraining supply to generation stations. 2016 has seen some of the worst bombing activities in the region and in turn led to an historic low in terms of energy generation in June 2016. All the thermal stations are located in the south of Nigeria, as shown in Figure 3-5.

3.2.1.3 Renewable energy generation

The national renewable energy action plan of Nigeria documents the government's policy of achieving a total generation capacity of 30GW by 2030, with at least 30% contributed from renewable energy (ICREEE, 2016). The projected installed capacity of renewable energy projects is 13.8GW, which is 43% of total installed capacity, 13% higher than the projected percentage contribution, revealing the government's ambition in this regard. A breakdown of the contribution by technology type is provided in Table 3-2. This is expected to increase the contribution of renewable energy to total generated energy from 4.7TWh (17% of total energy) in 2010 to 49.8TWh (31% of total energy) in 2030. This plan also aims to improve electricity access by increasing the electrification rate to 90% of the total population, while ensuring 10% of the rural population is served by hybrid renewable mini-grids, and a further 5% of the rural population served by standalone renewable energy systems.

Apart from hydro generation, there are no current grid connected projects for the other listed technology types in the renewable energy action plan. The potential of renewable energy resources in Nigeria covered in literature include; solar (Ojosu, 1990) (Fadare, 2009) (Heinrich Boll Stiftung and NESG, 2017), wind (Ojosu & Salawu, 1990) (Adekoya & Adewale, 1992) (Ohunakin, et al., 2011), bioenergy (Akinbami, et al., 2001) (Ohimain, 2010) (Mohammed, et al., 2014).

Table 3-2: 2030 Projected renewable generation capacity

Technology	2030 Target Capacity (GW)
Large hydro	4.7
Small and medium hydro	1.2
Solar PV	5.0
Solar thermal	1.0
Tidal	0
Wind	0.8
Bioenergy	1.1
Geothermal	0
Total	13.8

The most significant of the undeveloped renewable sources to Nigeria is solar, with a potential energy contribution of 207TWh/year with a 1% photovoltaic module (PV) land area coverage (Heinrich Boll Stiftung and NESG, 2017).

In support of this action plan, memoranda of understanding (MOU)s have been signed by the government, at state and federal level, for the development of solar and wind projects, and power purchase agreements (PPA) have been signed between the NBET and private companies for solar projects. At the distribution level, embedded renewable generation capacity and operation within each distribution company (DisCo) region fall under the embedded generation regulations of NERC (2012). It subjects all projects to regulations of the grid code with the exception of isolated independent distribution networks and stipulates projects above 20MW to be dispatched by the system operator.

To ensure liquidity and financial viability of the renewable projects, NERC has introduced the Renewable Energy Feed-in Tariff (REFIT) for biomass, solar, wind and small hydro energy generation greater than 1MW (NERC, 2015). Under the REFIT, energy purchase requires NBET and a DisCo to buy 50% each of the energy generation from the renewable energy supplier with a twenty-year purchase term.

A breakdown of the REFITs is given below in Table 3-3 and compared to the UK Feed-in Tariff (<1MW) (Office of Gas and Electricity Markets (OFGEM), 2016). Although the tariffs are slightly higher than that of UK and should inspire investor cost recovery confidence, transmission network constraints remain a significant challenge to growth of renewable energy in Nigeria (Office of Gas and Electricity Markets (OFGEM), 2016). Recently, 14 solar projects with a combined capacity of 1.1GW have signed PPAs with NBET (USAID, 2018).

Table 3-3 Renewable energy tariffs

Technology	Nigeria REFIT ($/kWh)	UK FIT ($/kWh)
Wind	0.13	0.10
Small hydro	0.15	0.10
Biomass	0.15	N/A
Solar	0.11	0.05

3.2.1.4 Off-Grid generation

Due to regular power cuts at the domestic level, most residential customers own diesel and petrol generators to power their homes during outages. Estimated off-grid energy generation was 12TWh/Yr. for 2014, which was 40% of the total energy generated (International Energy Agency, 2014). A survey by NOIPolls (2015), put alternative energy equipment ownership at residential level at 77% in 2015. GIZ, et al (2014) estimates 80% of Nigerians uses an alternate energy source such solar and generators. This report also estimates decentralised generation capacity at 2.6GW. A domestic household electrical equipment ownership survey for 837 respondents conducted as part of this research puts generator ownership at 87% (See Chapter 4). Self-generation is expensive at an average of 12cents/kWh compared to the average residential tariff of 6cents/kWh.

Similarly, commercial and industrial companies employ the use of diesel generators to provide electricity, increasing production costs and resulting in higher cost of goods and services.

3.2.2 Transmission

The transmission network is divided into 8 regions across all the states based on the locations of generation stations and 35 load centres. The current transmission grid capacity is estimated at 5.3GW with a network length of 15,000km and an estimated theoretical transformation capacity of 19GW (TCN, 2017). Comparing the transmission grid capacity to the total installed nameplate generation capacity of 12.4GW, the lack of transmission capacity poses a major challenge to the delivery of electricity.

A recent unpublished TCN sensitivity study puts current total transformation capacity at 10,200 MVA (8,178 MW) but with significant station limitations (TCN, 2017). According to Nigeria Electricity Supply Industry, NESI (2015), projected wheeling capacity is to be increased to 7.2GW and a network length of 21,000km.

Table 3-4 Electrical energy transmission (ONEM, 2011)

Energy (TWh)	2007	2008	2009	2010	2011
Energy injected	**22.1**	**21.1**	**19.8**	**24.0**	**26.7**
DisCos	18.4	17.1	15.4	19.9	21.6
International exports	1.0	1.0	1.1	1.3	1.7
Large Customers	0.3	0.2	0.2	0.2	0.2
Energy transmitted	**19.7**	**18.4**	**17.2**	**21.6**	**23.6**
Losses (%)	11.2	12.7	12.8	10.1	11.5

The NESI report also puts transmission losses at 7.4%, however there is no available data to independently verify it. Based on Table 3-4 above, the historical transmission loss average is 11.6% as suggested by the market operator. The Multi-Year Tariff Order II (MYTO II) tariff calculation sheet puts projected loss reduction at 8.05% between 2012 and 2041 (NERC, 2015).

Nigeria has fixed bilateral electricity export agreements with 2 countries, NIGELEC of Niger Republic (95MW) and CEB of Benin Republic (200MW) via 330kV single circuit lines. As of the 2011, TCN also supplies 3 large aluminium-smelting companies (ONEM, 2011).

3.2.3 Distribution

11 distribution companies, each with a locational monopoly in different regions, serve 6.4 million customers (residential and non-residential) in Nigeria (NERC, 2015). Customer categorisation is based on customer class and billing type. Further sub division of the customer class is based on the rated power of connection of the customer to the distribution network, which determines the tariff class. Billing type classifies customers as either pre-paid or post-paid. Categorisation is listed below based on the customer class and power network connection level.

1) Residential:
    i. R1: Life-Line(50kWh/month)
    ii. R2: Single and 3 Phase
    iii. R3: Low Voltage maximum demand
    iv. R4: High Voltage maximum demand (11/33kV)
2) Commercial
    i. C1: Single and 3 Phase
    ii. C2: Low Voltage maximum demand
    iii. C3: High Voltage maximum demand (11/33kV)
3) Industrial
    i. D1: Single and 3 Phase
    ii. D2: Low Voltage maximum demand
    iii. D3: High Voltage maximum demand (11/33kV)
4) Special (Hospitals, Government agencies etc.)
    i. A1: Single and 3 Phase
    ii. A2: Low Voltage maximum demand
    iii. A3: High Voltage maximum demand (11/33kV)
5) Street Lighting
    i. Single and 3 Phase

3.2.3.1 Electrification Rate

According to the IEA (2014), the electrification rate in Nigeria is 50%, compared to a 57% for Africa and 32% for Sub-Saharan Africa. A different report, the 2013 National

Demographic and Health Survey report of the National Population Commission puts access to electricity ratio at 56% for Nigeria (National Population Commission (NPC) and ICF International, 2013). Urban access ratio is 83.6% and rural access ratio is 34.4%. Urban households make up 34% of the population, while rural households make up 66%.

Table 3-5 below shows that the electrification rate, as at 2009, was 62.9% with the DisCo connection rate at 51.3%. The difference between the calculated connection rate and data from NBS may be attributed to illegal connections, that is, there are more connections to the distribution networks than the DisCos are accounting for. The difference, which is the equivalent of 16million customers, shows a large gap in the coverage by DisCos. This challenge is further compounded by the metering rate of 52% among all customers (Vanguard Nigeria, 2016).

Table 3-5 Electrification rate in Nigeria (%) (NBS, 2012)

	Year				
Electricity source	2005	2006	2007	2008	2009
DisCo	43.6	39.6	47.3	41.3	51.3
DisCo/Private	4.3	2.2	5.8	7.4	7.6
Private Only	3.4	1.8	2.7	3.2	3.0
Electrification rate	52.3	44.4	56.8	51.9	62.9

3.2.3.2 Energy Distribution

Data on historical energy extracted by DisCos has been obtained from the Market Operator. PHCN, the defunct power utility company, is the source of additional data through its 2009 National Load Demand Study (Power Holding Company of Nigeria, 2009). The current load allocation methodology supplies a class of load known as exempted load first, before the remaining power is allocated to DisCos based on a tariff percentage basis and Key Performance Indicators (KPI) metrics. The KPI metrics include percentage loss reduction, increase in metering efficiency, network expansion, customer satisfaction index and distribution capacity. The exempted load includes international exports and load reserved for voltage and frequency control.

Average historical percentage energy extraction from the grid is presented in Table 3-6 below, along with the system operator (SO) load allocation percentages (ONEM, 2011). A breakdown of percentage energy use by customer class is presented in Table 3-7 (NERC, 2015).

The average annual extraction of the DisCos from the grid shows Ikeja DisCo with the highest at 14%, and Yola DisCo with the lowest at 2%. Eko, Ikeja, Kano and Port Harcourt DisCos have the highest Industrial energy usage, which agrees with the volume of manufacturing and processing activities in the 3 major cities under their respective coverage; Lagos, Kano and Port Harcourt. Abuja DisCo, which supplies the country capital along with 3 other states, has the lowest Industrial energy usage, as most of the customers in this region are residential and commercial. Abuja FCT, its largest market with 87% of energy allocation, consists mostly of residential homes, commercial and government administrative buildings. Abuja and Ikeja DisCos have the highest percentages of commercial energy usage reflecting significant levels of commerce influenced by the geopolitical history of the cities they supply. Abuja FCT is the current country capital, and Ikeja in Lagos, was the former capital.

Table 3-6 Average Energy Allocation to DisCos (%)

DisCo	Allocation	Extraction
Abuja	12	11
Benin	9	12
Enugu	11	10
Eko	9	10
Ibadan	13	12
Ikeja	15	14
Jos	6	5
Kaduna	8	7
Kano	8	4
Port Harcourt	7	6
Yola	4	2

Sectorial energy use in Nigeria reveals a low level of industrial energy consumption. This can either be interpreted as the industrial sector generating most of its energy needs off-grid, translating to a higher cost of goods and services (NESI, 2015), or the inadequate energy supply in the country not encouraging industrialisation.

The second interpretation agrees with prior analysis presented in GIZ (2014), which showed that energy generation increased over the decade between 2001 and 2011 by a factor of 2.6, while industry grew by a factor of 3.5. This correlation between energy and the industry sector shows that energy supply resulted in a small increase in industrial output over the ten-year period. Table 3-8 below shows Nigeria's customer class percentage energy consumption in comparison to other developing countries and the United Kingdom.

Table 3-7 Energy use by sector (%)

DisCo	Residential	Commercial	Industrial	Others
Abuja	64	31	1	3
Benin	73	12	13	2
Enugu	69	13	14	4
Eko	56	11	30	2
Ibadan	61	12	21	5
Ikeja	52	21	23	4
Jos	65	14	8	13
Kaduna	68	13	12	7
Kano	62	9	23	6
Port Harcourt	66	13	17	5
Yola	59	11	14	15
Average	63	15	16	6

Table 3-8 Comparison of sectorial electrical energy use among countries

Country	GDP ($Trn.)	Energy (TWh)	Residential (%)	Commercial (%)	Industrial (%)
Nigeria	0.5	30	63	15	16
S/Africa	0.3	237	37	11	43
Indonesia	0.9	203	39	24	37
Brazil	2.2	531	25	25	45
UK	2.3	330	30	26	36

Sources: (PLN Indonesia, 2015) (The World Bank, 2015) (Department of Energy, Republic of South Africa, 2011) (Office of Strategic Energy Studies, 2014)

It can be seen that Nigeria's overall energy use and industrial energy consumption share of 16%, is less than its peers and other developed countries, which have an average of 40%. In order for Nigeria to achieve industrialisation and grow its economy, it is imperative that energy supply increases significantly.

3.2.3.3 Distribution losses

Technical, commercial and collection losses constitute the energy losses at the distribution level. Historical underinvestment in this sector saw the gradual decay of infrastructure and decline in maintenance of equipment. As part of the privatisation agreements, the technical bids submitted by investors for the DisCos contain network performance covenants that will see an annual reduction in aggregate technical commercial and collection (ATCC) losses (NERC, 2015). Table 3-9 shows the current ATCC losses for DisCos based on data from NERC and company reports (NERC, 2015).

Table 3-9 Losses at Distribution level

	Losses (%)		ATCC (%)	
DisCo	2015 Actual	2024 Target	2015 Actual	2024 Target
Abuja	13.4	4.8	52.8	19.3
Benin	13.0	3.8	53.7	16.5
Enugu	14.6	2.8	49.1	9.4
Eko	12.8	4.8	28.3	10.3
Ibadan	10.7	3.9	42.5	15.4
Ikeja	10.7	3.1	32.2	9.2
Jos	12.0	5.4	58.0	26.2
Kaduna	13.5	1.4	48.4	4.9
Kano	13.5	4.4	45.1	14.7
Port Harcourt	10.7	4.0	55.4	20.5
Yola	13.7	5.9	57.6	24.9
Average	12.5	4.0	48.9	15.9

It can be seen that the ATCC at the distribution level is about half of the total energy extracted from the grid by the distribution companies. The challenge of effective metering of customers contributes significantly to commercial losses, as many DisCos are not able to monitor, and bill energy sold efficiently. DisCos have resorted to the use of estimated bills, and in most cases, customers refuse to pay those bills resulting in collection losses. Frequent load shedding and inefficient bill reading of post-paid meters has created an air of distrust between customers and DisCos with many customers challenging their bills. There are also illegal extractions of energy along various lines in their respective networks contributing to losses.

It is believed that with an increased penetration of pre-paid and smart meters among customers, commercial and collection losses will be reduced significantly. Investment in distribution network infrastructure will also see a reduction in technical losses.

3.3 Demand

The inability to meet demand due to generation inadequacy means that the peak demand for Nigeria is unknown. Typically, peak demand in Nigeria is described in terms of the historical maximum recorded generation capacity, as demand is more a function of generation availability than it is of electricity usage. The highest recorded peak demand for each DisCo is presented in Table 3-10 (NESI, 2017). The demand figures range from the highest of 849MW in Ikeja DisCo, to the lowest of 198MW in Yola DisCo. While the demand capacities of DisCos are believed to be higher than the figures presented below, generation and transmission constraints mean their individual peak demand remain unserved (NESI, 2015).

Table 3-10 Peak Demand by DisCo

DisCo	Demand (MW)
Abuja	651
Benin	509
Enugu	509
Eko	622
Ibadan	736
Ikeja	849
Jos	311
Kaduna	453
Kano	453
Port Harcourt	368
Yola	198
Total	5,660

3.3.1 Suppressed Demand

The estimated system simultaneous peak demand is presented in Table 3-11. The load factor has been calculated using historical generated energy values and the simultaneous peak load value. Due to unavailable data on the historical energy sales, the historical energy supply data has been used for exports and large customers (ONEM, 2011).

Based on the above estimation, the system peak load capacity is 6.4GW. Table 3-12 below shows a recent historical trend in the annual average available generation capacity to supply the above load estimates. From the table it can be seen that the average available generation capacity of 4.5MW (average effective capacity - 3.2MW) is lower than the system "peak load" of 6.4MW. This results in frequent load shedding and rolling blackouts across the country due to the mismatch in generation and demand, with network outages also experienced due to frequency collapses. An historical system collapse trend between 2012 and 2015 (January to August) is presented in Figure 3-9 (NESI, 2015). Although a declining trend is observed from 2014, with at least 5 annual outages over the period, it shows the inability of the current system to supply demand.

Table 3-11 Estimate System Peak Load

Off-taker	System Peak Load (MW)	Load Factor (%)
DisCo	5,660	62
Exports - CEB	200	87
Export - NIGELEC	95	69
Large customers	90	35
Transmission Losses	312	78
Average	6,357	66

Table 3-12 Historical Generation Capacity (MW)

	Capacity (MW)		
Year	Available	Effective	Constrained
2012	4,940	3,106	1,834
2013	4,515	3,106	1,409
2014	4,068	3,201	867
2015	4,419	3,361	1,058

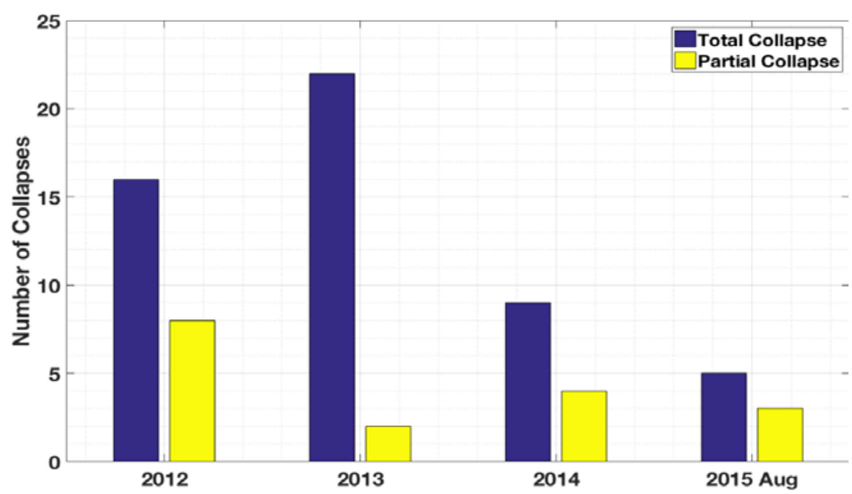


Figure 3-9: Annual frequency of system collapse

Load shedding is implemented at both the transmission and distribution levels of the network. A daily hourly load allocation and load shedding instruction is issued by the SO to all distribution companies, for frequency management on the network. Network constraints experienced by distribution companies, also results in the rejection of power supply allocated to them, typically at an average of 20% (TCN, 2017). Further load shedding is undertaken by the DisCos to manage their networks, and one of the load shedding criteria distribution companies' use is bills collection rate. Areas with the lowest bills collection loss rate are served before other areas and enjoy longer supply hours.

Daily power cuts vary across the country, as the outages are sporadic with different load management programmes implemented across the distribution companies. The frequency and duration of outages varies across DisCos and customers resort to the use of back-up diesel generators and solar inverters for electricity.

3.3.2 Load Curves in Nigeria

Constraints in the power generation, transmission and distribution segments of the Nigerian power network result in an inadequate supply of electricity across the country. In a bid to manage the limited power supply, the distribution network operators employ load shedding as a network management tool, ensuring limited power supply is served to customers, even though the supply might be intermittent. The load shedding, which can either be pre-planned or arbitrary depending on power supply, network and revenue recovery conditions, occurs at the different voltage levels of the network; 33/11kV, 33/0.415kV and the 11/0.415kV (Adegbulugbe, et al., 2007). Each DisCo made up of business units (33/11kV level) gets a load allocation from the system operator (SO), this allocation is then sub allocated by the DisCo network operator to each business unit made up of undertaking offices (415V level) (TCN, 2017). The undertaking offices then determine which customers are supplied electricity by controlling customer supply point transformers.

From the transmission and distribution network perspectives, the network supply constraints result in an irregular load pattern unrepresentative of typical time sensitive changes in demand, and an unknown peak demand.

Load patterns from three business units in one of the eleven DisCos in Nigeria, are shown below in Figure 3-10 to Figure 3-13 (NERC, 2015). The figures represent the mean daily demand and load duration curves for each business unit. The load duration curve is a graph of the load in a descending order of magnitude to show the time duration a given magnitude of load is exceeded. The impact of load shedding and forced outages is shown at different points in the same network. Business Unit A, in Figure 3-10, represents the aggregate mean daily and load duration curve across six 33kV feeders and one 11kV feeder from October 2015 to September 2016. Business Unit B, in Figure 3-11, represents the aggregate mean daily and load duration curve across three 33kV feeders from January 2016 to October 2016. Business Unit C, in Figure 3-12 and Figure 3-13 respectively , represents the aggregate mean daily and load duration curve in a 33kV feeder, from January to April 2015 and September to December 2015.

Forced outages and load shedding causes zero demand measurements at different points in Business Unit A. Prolonged periods of suppressed demand (total blackout) are observed, representing the months of November 2015 and June 2016. There is total suppressed demand for 2764 hours, resulting in a total disconnection rate of 31% for the period. In Business Unit B, while the suppressions in peak demand as a result of load shedding is observed across the plot, a period of sustained load shedding is particularly apparent for a prolonged period, representing May and June 2016. Total disconnection rate for the period is 11%. For Business Unit C, apart from March 2015 when the load supplied was 0.3MW, a load shedding of 0.2MW occurred between January and April 2015.

The load shedding trend continued for the rest of the year, except for one day in October 2015, which saw demand increased to 2.2MW. The actual measured peak demand for Business Unit C is 5.7MW. The total disconnection rate is 70% and 29%, for the January to April period, and September to December period, respectively.

The load duration curves observed above are not similar to typical load curves obtained in networks served by constant unconstrained power supply (Independent Market Operator, 2014). For this DisCo, data availability has limited the presentation of load shedding results to only the 33kV and 11kV load voltage levels, even though this phenomenon occurs further downstream at the 415V level.

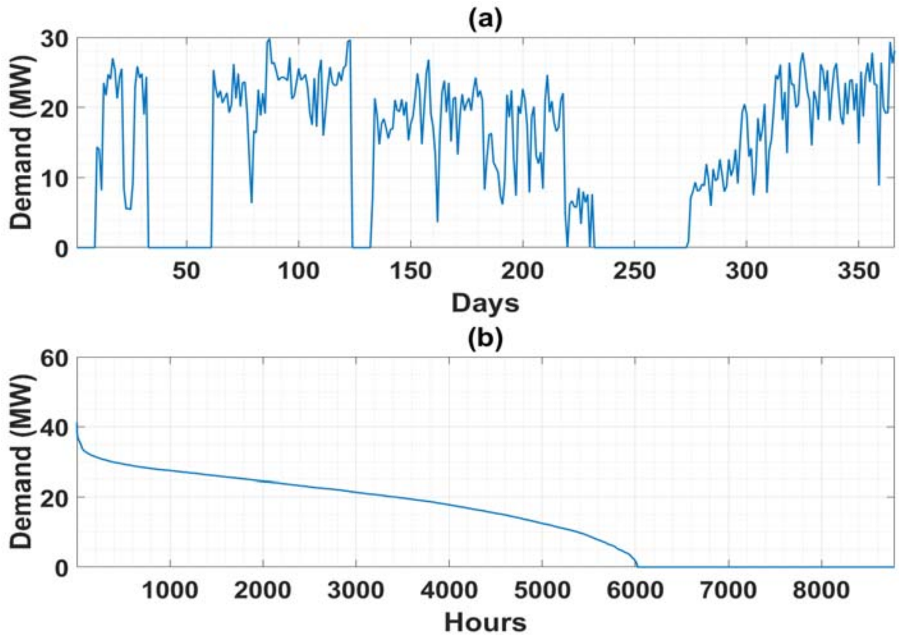


Figure 3-10 : Business Unit A (a) Mean Daily Demand (b) Load Duration Curve

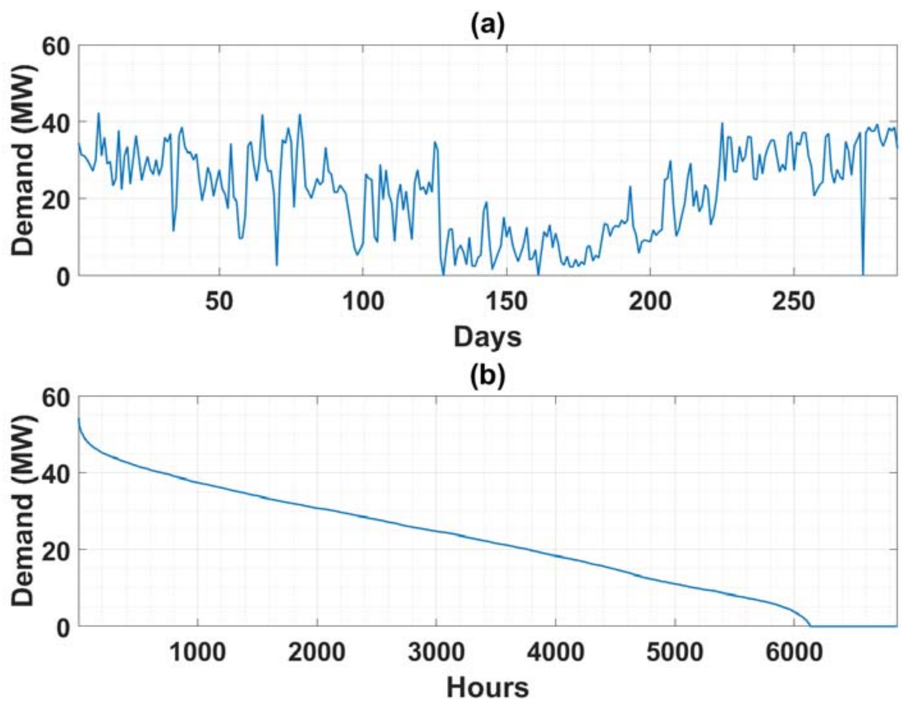


Figure 3-11: Business Unit B (a) Mean Daily Demand (b) Load Duration Curve

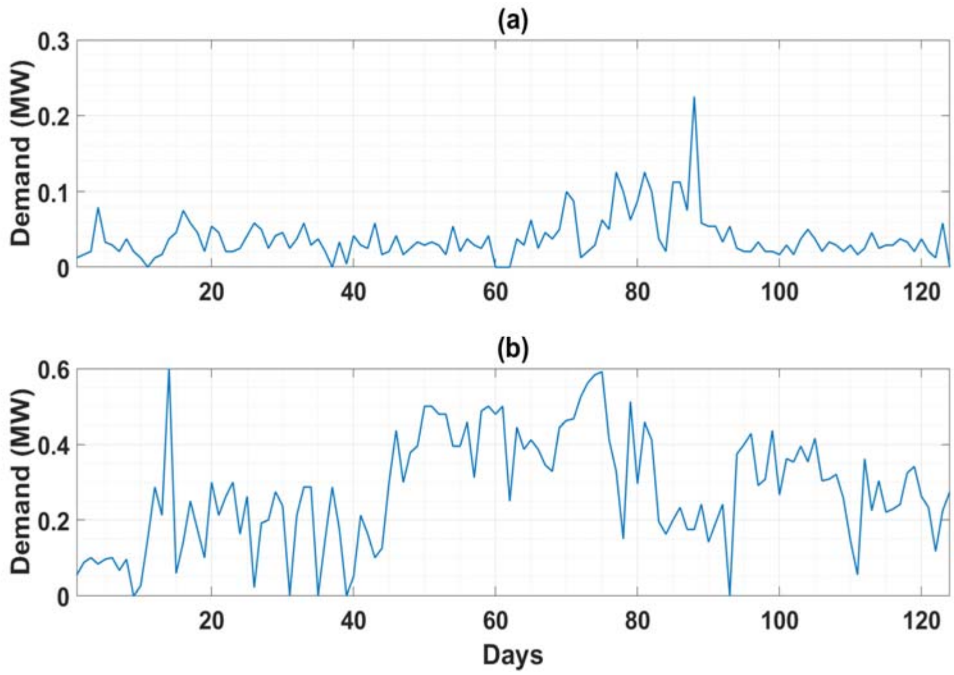


Figure 3-12: Business Unit C – Mean Daily Demand (a) January to April (b) September to December

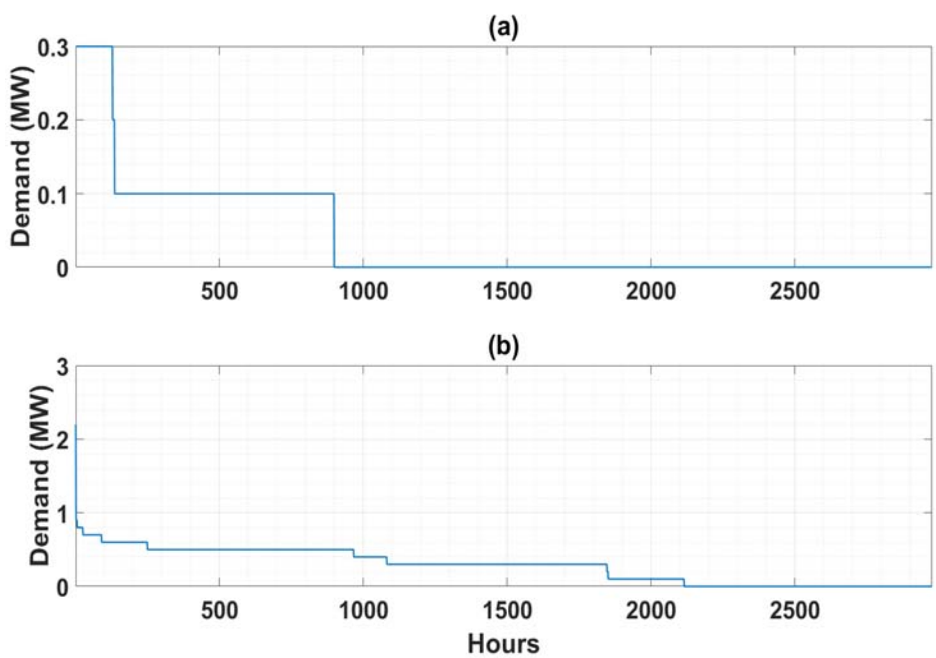


Figure 3-13: Business Unit C – Load Duration Curve (a) January to April (b) September to December

At the transmission grid level, the inability of generation to meet demand means the system load extracts all the power generated. Figure 3-14 shows a load curve for a typical day in Nigeria in 2014 (TCN, 2017). The system load curve for Nigeria does not reflect the regular variations such as morning and evening spikes. The load curve is flat, reflecting available generation capacity, with intermittent peak load and no off-peak declines.

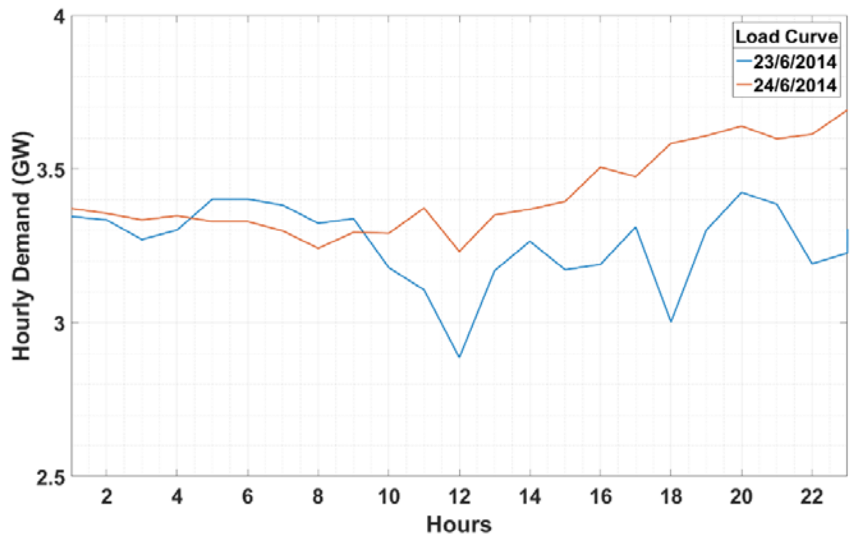


Figure 3-14 Sample daily load curve for Nigeria

3.3.3 Demand Forecasts

Performing electricity demand forecasts for Nigeria is a challenging exercise due to the determination of independent variables for the forecasting analysis that minimise the bias impact of load shedding on available demand data. Akinlo (2009), Ekpo, et al., (2011) and Iyke (2015) investigated the relationship between energy consumption and various drivers including gross domestic product (GDP), price and population. While all three studies establish a measure of relationship between energy and GDP, Akinlo (2009) highlights the possibility of potential bias due to the bivariate analysis used in that study and also of the influence of load shedding on the sample data. In a similar study, Akpan and Akpan (2012) establish no causality between electricity consumption and economic growth using historical demand data (1970-2008).

For national forecasts, Ibitoye and Adenikinju (2007) use a disaggregated bottom up approach to forecast sectoral demand but neglected historical data due to the influence of suppressed demand and system losses on the past demand. Mati, et al., (2009) performed a time series regression using historical demand data (1970-2005), observed an incoherent trend in the data set, and concluded on the inadequacy of time series modelling for Nigerian demand.

To date, three independent long-term bottom-up electricity demand studies have been carried out for Nigeria: a 2006 study was carried out by the Energy Commission of Nigeria (ECN), a 2008 study was carried out by the defunct power utility company, PHCN and recent study commissioned by TCN but leans heavily on the 2008 study methodology. 2030 Forecasts for all studies are presented in Table 3-13 (Power Holding Company of Nigeria, 2009). The 2006 and 2008 studies are described below.

1) ECN 2006 demand study: This study was based on econometric and end-use models using the Model for Analysis of Energy Demand (MAED) by IAEA. Future energy demand is evaluated based on socioeconomic, technological and demographic development. Energy demand is disaggregated into the following sectors; industry, services, transport and household. Total energy demand is calculated by multiplying base year energy demand by an annual modifier. This modifier is based on data such as socioeconomic variables and energy efficiency targets.
2) PHCN 2008 demand study: This study was carried out by foreign consultants with international network study experience. The study was based on trend analysis and medium voltage distribution analysis. It used global and regional approaches to demand forecasting. Global forecasting consists of a regression model based on historical peak demand and an estimation of suppressed load at the national level. Regional forecasting is similar to global forecasting but done at the distribution level, employing an econometric forecasting method to predict customer class demand evolution based on GDP and electrification rates.

Both studies were limited by demand data and recorded network constraints. Limitations of both studies are analysed below.

1) ECN 2006 demand study: Extensively limited by data required for sectorial energy projections as some sectors were left unpopulated. The load curve was

limited in its use due to frequent system collapses in the base year of study. Load data at customer level was also unavailable for the simulation of consumer class load curves.

2) PHCN 2008 demand study: Limited by data but performed analysis based on collected network data at distribution level. Energy consumption data, transformer and feeder readings were obtained to estimate demand in each distribution area. However, analysis was constrained by limited equipment coverage, low electrification rate and constrained grid supply. Load curve analysis was based on feeder readings in areas with a predominance of each customer class. However, this analysis did not consider the influence of weather on demand, was constrained by time and further limited by load shedding.

The disparity in scenario forecasts for both studies reveals the challenges in estimating demand for the country. In both studies, scenarios were defined with assumptions based on economic and socioeconomic growth.

Table 3-13: 2030 Demand forecasts for Nigeria

	2030 Forecast (GW)		
Scenario	ECN 2006	PHCN 2008	TCN 2017
Low	19.9	15.9	N/A
Medium	33.0	24.2	N/A
High	73.9	43.1	35.1

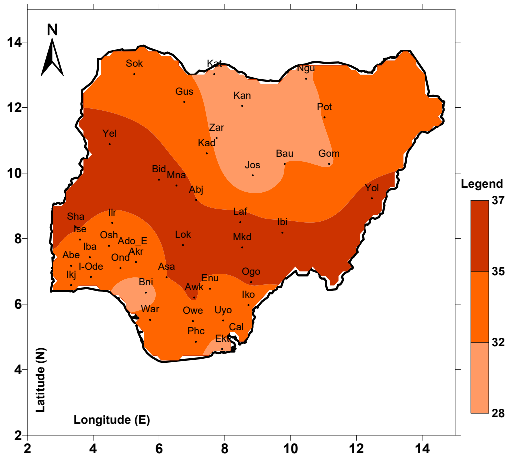
Metrics such as economic growth, electrification growth rate and power sector investment assumed in both the 2006 and 2008 studies, which are key to delivering the above forecasts have not been realised. While a lower 2030 forecast has been projected in the 2017 study, it uses similar metrics as the other studies and does not account for the impact of weather on demand. It is therefore necessary for a new load demand study to be carried out for Nigeria, using current energy consumption and socioeconomic indicators. The absence of weather analysis in the three studies reveals the need for a demand study that evaluates seasonal temporal influences on electricity use in Nigeria.

3.3.4 Influence of weather on demand in Nigeria

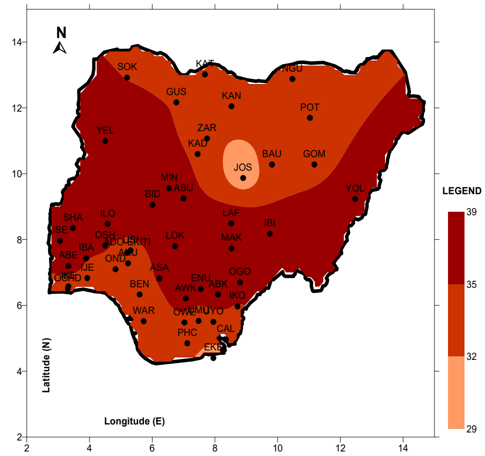
With maximum temperatures reaching as high as 41.1°C in parts of the country, air-conditioner ownership among wealthy households is common, although its use is affected by price and power supply (Adaji, et al., 2016). Usage rate varies across the country due to electricity costs, health and weather, but it was found to have a national average usage rate of 22% (Energy Commission of Nigeria; United Nations Development Programme; Federal Ministry of Environment; Global Environment Facility, 2013). This shows that Nigeria's electricity demand is potentially sensitive to weather.

Figure 3-15 shows the maximum temperatures across the country for the first three months of the year (The Nigerian Meteorological Agency, 2014). Nigeria has two seasons, rainy and dry. The dry season occurs between December and March, while the rainy season occurs between April and October. However, the rainy season onset date varies among the states. While the coastal regions experience mild temperature changes during the seasons, the northern regions experience extreme temperature changes during the dry season. Maximum temperatures occur between January and April, which are the hottest months of the year, with a maximum temperature peak of 41.1°C in April. From January, it can be observed that the middle belt of the country experiences the hottest temperatures, and this trend continues into February, expanding to other states on the east and west borders of the country. By March, the maximum temperatures have shifted to the extreme north-east and north-west regions of the country, with the middle belt and southern regions, experiencing lower temperatures.

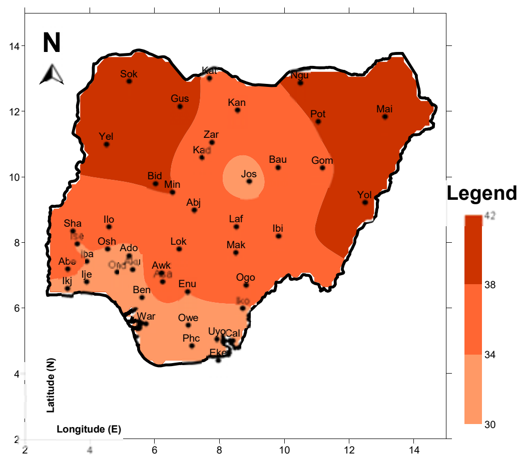
While the example of seasonal temperature changes has been discussed, the seasonal daily changes are just as significant (Ogbonna & Harris, 2008) (Ayinla & Odetoye, 2015) (Adunola & Ajibola, 2016).



(a) January



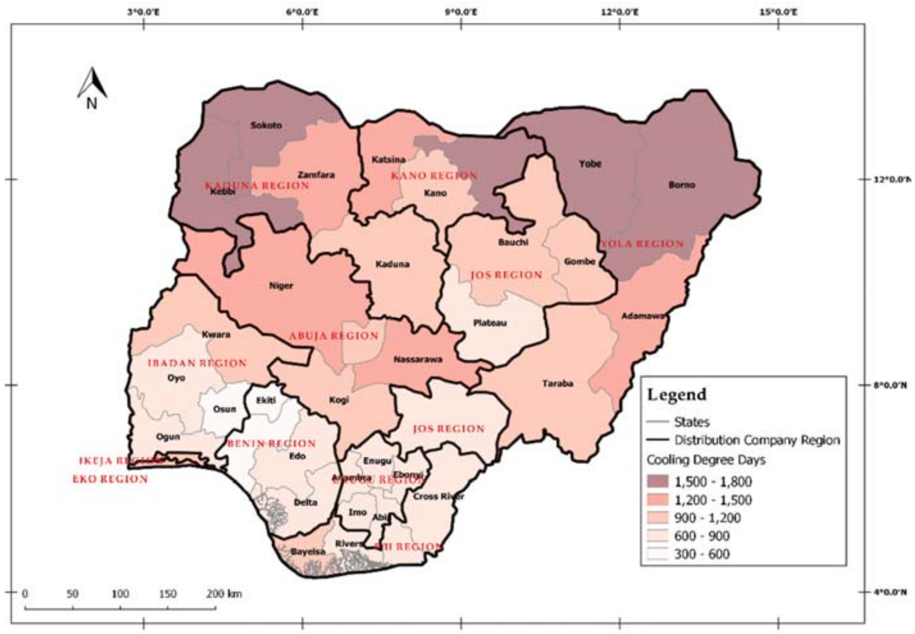
(b) February



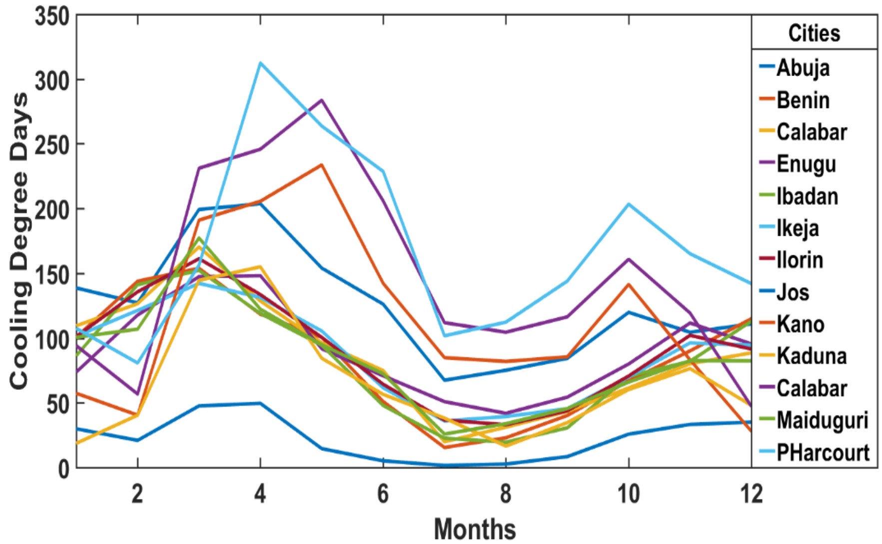
(c) March

Figure 3-15 Maximum Temperatures across Nigeria (Q1 2014)

Figure 3-16 presents cooling degree-days (CDD) plots for Nigeria. Figure 3-16(a) shows the annual CDD for Nigeria using a base temperature of 24°C, and three years of temperature data from the Nigeria Meteorological Agency (NIMET). Figure 3-16(b) shows the results of a model developed by Olorumaiye (2001), used to estimate the monthly CDD for 11 selected Nigerian cities using 15-year average monthly temperature data.



(a)



(b)

Figure 3-16 Cooling Degree Days for Nigeria
(a) Annual CDD (b) Monthly CDD for selected cities

The Annual CDD map shows that the expected cooling requirement in Nigeria increases in the northward direction. While the northern states of Borno, Kebbi, Sokoto and Yobe have the highest CDD values, Ekiti, Osun, Ondo in the south-west and

Plateau in the north-central have the lowest CDD values. The coastal regions also experience a lower cooling requirement than the land-locked regions further north. It is therefore expected that the cooling demand for Nigeria will vary among the states based on weather variables such as temperature. From the monthly CDD analysis, it is observed that the CDD has its highest values during the first quarter of the year, which is the harshest period of the dry season, and experiences a decline during the rainy season, rising again at the start of the dry season in October. It is also expected that Nigeria will experience increased energy demand during the first quarter of the year as the need for cooling increases due to the increased temperatures. However, this period of increased demand coincides with the months Nigeria experiences its lowest energy generation due to declining inflows into the 3 hydro dams as discussed in section 3.2.1.1.

Based on this observation, it is important that power planning studies for Nigeria account for the impact of weather on power generation and demand. There are currently no studies that assess the relationship between weather and electricity demand for Nigeria.

3.4 Research needs

In a power network where load shedding is a constant feature, load curves are more representative of available supply than peak demand. For effective network management and planning, representative demand curves are imperative to determine the generation capacity required to serve the demand. The system operator also requires detailed demand information to determine the least cost energy mix required from energy producers to meet demand. In Nigeria, this information is particularly important because the current tariff pricing mechanism and system operator load allocation schedule assumes a fixed annual peak demand for each DisCo (Adegbulugbe, et al., 2007). A dynamic load allocation schedule for the DisCos will improve network planning and reduce the penalties associated with the over extraction of energy at network boundary points as stipulated in the Load Allocation, System Operator's Instructions and Grid discipline order, of the current Multi-Year Tariff Order (MYTO) 2.1, whereby DisCos are liable to twice the energy imbalance cost (Adegbulugbe, et al., 2007). Also, load studies such as the PHCN 2008 which employ the measured feeder readings to estimate peak demand have a high risk of underestimating demand due to the resultant effect of demand suppression at the lower voltage levels served by the feeder.

Based on the government's plan to rapidly expand the power system, with a key focus on renewable generation capacity, a reliability and generation adequacy analysis is required to assess the current grid connected power plants and measure the reliability impact of renewable energy generation on grid supply. While a deterministic reliability approach is usually undertaken by TCN, a probabilistic generation adequacy analysis is required due to the various uncertainties inherent in Nigeria's power system including the operational efficiency of existing power generation stations and power supply constraints. Furthermore, generation adequacy in a deregulated market should account for the uncertainty in power production from independent producers, as the efficiency incentivisation created in a competitive energy supply market, is traded for market liquidity security in a purchasing agency structure. The reliability analysis should assess the temporal and peak characteristics of demand, allowing for the influence of weather; the time varying nature of renewable energy resources; the probability of generation availability, in the determination of generation adequacy.

To this end, a methodology is required to estimate spatial peak demand, as well as time series demand data, unconstrained by suppressed demand. This task is made complex due to the different climatic zones that can be found across the country. A spatial weather sensitive electricity demand model is thereby required to estimate the aggregate electricity demand for Nigeria.

3.5 Summary of Chapter

This chapter provided an overview of the Nigerian electricity industry and discussed the roles of its key actors. An analysis of power supply was presented, and the performance of the main sectors was described. The characteristics of demand, its future projections, and the impact of weather on demand were also discussed. In particular, the chapter noted the lack of a definitive demand profile for Nigeria due to limited capacity of generation.

Chapter 4
Modelling
Residential Electricity Demand

The aim of this chapter is to develop and discuss a model for simulating residential electricity demand for Nigeria. The adopted methodology for this study is based on the review of various modelling techniques and is also influenced by the limited availability of electricity demand data from Nigeria. A weather sensitive stochastic model capable of simulating residential electricity demand for all states in Nigeria is developed and presented. Validation of the model is done using measured residential electrical demand information from Nigeria.

4.1 Modelling Approach

Due to the tropical climate and high temperatures across different regions in the country, the potential influence of weather on demand requires that the selected demand estimation methodology captures the impact of cooling demand on energy consumption. As a building block for this analysis, bottom-up domestic energy consumption modelling was chosen due to high similarity of electrical equipment ownership and energy use requirements in the residential sector. The scale of domestic energy to non-domestic energy consumption is shown in Table 3-7. The heterogeneous nature of energy use, electrical equipment, and sectorial behaviour in the commercial and industrial sectors would require an intensive modelling exercise currently beyond the scope of this study. Non-domestic energy use is modelled using assumptions based on an energy measurement campaign in Nigeria and discussed further in Chapter 5. A key feature of bottom-up engineering models for residential modelling is the modelling of household occupant behaviour. An occupant activity is the key driver of electrical energy consumption, as it determines usage of owned electrical appliances. The aggregate use of electrical appliances in a household is what contributes to its total electrical energy consumption. The household's energy meter records this data and a summarised version is provided to the occupants as an energy bill from the energy supplier. The initial planned approach to collating residential demand data was to obtain metered consumption data from houses in Nigeria. Data sourced via this approach would reveal activity patterns through load duration curves at household level, provide insight into the diversity of seasonal load patterns across households and the coincident nature of peak demand across selected households. Bartels and Feibig (1996) used metered data from 250 households in Australia to simulate load curves, McQueen, et al. (2004) used measured 10-minute resolution energy data from 21 houses in New Zealand to forecast maximum demand and Ramirez, et al. (2005) used measured data from 2,800 commercial premises comprising 18,500 buildings to simulate energy consumption in commercial buildings.

Between 2012 and 2013, the United Nations Development Programme (UNDP), led a one-year residential metering campaign in Nigeria for 230 households (United Nations Development Programme, Energy Commission of Nigeria, Federal Ministry of Environment, Global Environment Facility, 2013). In 6 states, 35 households were monitored for one month, and in an unnamed location, 20 households were also monitored for one year. The frequency of measurements was at 10 minutes intervals. With separate measurements taken for only the household energy meter, AC, cold appliances and lighting, over half of the measured energy cannot be explained. Household access restrictions, monitoring equipment configuration and installation difficulties, as well as complicated and unlabelled residential distribution boards were some of the identified challenges recorded during the metering campaign. The report also fails to provide any details on the household types selected for the monitoring campaign. The proportion of unexplained energy demand per household and information on households used in the study, significantly limits its application in extrapolating demand for Nigerian residential customers.

Similar residential energy measurement campaigns typically contain information on the characteristics of households used for the study, and the energy consumption information is presented by household type, i.e., by building type; detached house or occupant type; households with children (Department of Energy and Climate Change, Intertek Testing and Certification Ltd., 2016), (Widen & Wackelgard, 2010). For Nigeria, extrapolation using metered data would require demand estimates for each of the residential tariff classes, and by building type. With the required information unavailable from the report and considering the funding, logistics and manpower challenges in executing a similar study, it necessitated an alternative approach to estimate the data. The adopted approached involved building a weather sensitive model capable of simulating energy use in typical Nigerian households across the different tariff classes. While modelling of residential energy demand is one area that has been covered extensively in literature Capasso, et al., (1994), McQueen, et al., (2004), Paatero and Lund (2005), Richardson et al., (2010), Widen and Wackelgard (2010) and Colin, et al., (2014), the temperate climate and economic parameters factored into the development of those models significantly differ from the tropical weather and socioeconomic considerations required for modelling Nigeria's residential electricity demand. As such a simple translation of these models would not be credible.

To aid the development of this model, a Time Use Survey was required (Centre for Time Use Research, 2011). This is a detailed survey of household activities, which can be used in building household activity profiles (Richardson, et al., 2010), (Collin, et al., 2014). Such a survey was not publicly available for Nigeria (United Nations Statistics Division, 1998). Therefore, a survey was conducted in Nigeria to obtain information on household energy usage. The use of surveys to estimate energy use is one that has been employed in sub-Saharan countries with energy supply shortages. In Cameroun and Botswana, surveys have been used to estimate energy use for the industrial and residential sectors respectively (Thomas, et al., 2010), (Ofetotse, et al., 2015).

The questionnaire requested the preferred times of performing basic household activities during periods of power supply. To make this manageable for those doing the questionnaire a half-hourly resolution was used. It also gathered data on appliance ownership, building types, occupancy and tariff class among others. Consequently, the questionnaire results were considered sufficient in order to build realistic activity patterns and household profiles. While household activity times as recorded by respondents in the questionnaire may differ in practice, across a large number of respondents, a concentration of activities was anticipated to occur around similar times mitigating this concern.

A concern with the use of metered data from households that experience frequent load shedding is the shifting of household demand to periods of restored power supply; this tends to inflate demand during periods of power supply uncertainty. The questionnaire was formed such that participants should detail what they did when supply was available. Using activity diaries and questionnaires eliminates this risk, as the activities are better distributed throughout the day and not impacted by load shedding.

Modelling the influence of weather on electricity demand has been achieved by using hourly satellite re-analysis temperature and irradiance data.

An overview of the modelling approach is shown in Figure 4-1. A household profile, with information including occupancy and appliance ownership, is generated using input data obtained from the survey results. The household activity is simulated using the activity diary results from the survey. The household profile data is then converted to electricity demand using the appliance and air conditioner models. The weather data input is used to simulate the external weather conditions.

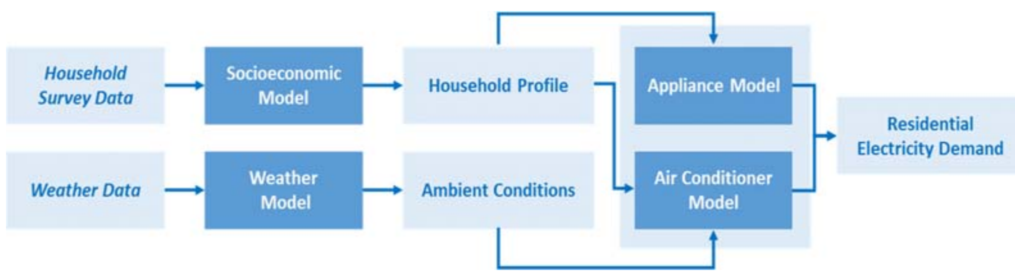


Figure 4-1: Overview of Modelling approach

4.2 Household Survey

The survey which was carried out in Nigeria between March and May 2016, focused solely on residential customers. It was achieved using two methods, a face-to-face questionnaire and an online survey. Due to limited time and manpower resources, it was essential that the developed questionnaire was not overly detailed and cumbersome for respondents, but at the same time, was able to capture key data for the model development. While executed during the dry season, the seasonal bias on the results is negligible as the questionnaire sought to capture household behaviour in constant power supply conditions. However, the survey could also be conducted in the rainy season to evaluate any changes in seasonal patterns which can be included as part of future work. The factors considered in developing the questionnaire are discussed in the next section.

4.2.1 Factors affecting residential electricity demand

Various factors determine the electrical demand at the residential level and can broadly be classified into 2 categories, which are socioeconomic and technical.

1) Socioeconomic factors: Household size has been well proven to impact energy consumption. Yohanis, et al., (2008), Leahy and Lyons (2010), Ndiaye and Gabriel (2011) and Jones and Lomas (2015) have all revealed a positive relationship between household size and energy use, with Zhou and Teng (2013) revealing an 8% increase per household member. However, for large households, Chen, et al. (2013) established a negative correlation between family size and energy consumption per capita as sharing of appliances means bigger families use less energy per capita than smaller families. Shittu, et al. (2004) did not find any significant relationship between household size and household expenditure on energy in Nigeria. Ogwumike, et al. (2014) did not find any statistical significance in the relationship between household size and electricity use based on Nigerian National Bureau of Statistics 2004 Living Standards Survey data for Nigeria.

   Household income has also been revealed to influence electricity consumption, (Weismann, et al., 2011), (Sanquist, et al., 2012), (Bedir, et al., 2013). Households with higher income levels purchase more appliances (Haas, et al., 1998) and appliances with higher power ratings than households with lower income levels (Santamouris, et al., 2007). Other researchers have discovered a positive relationship between energy consumption and income levels (Yohanis, et al., 2008), (Wyatt, 2013). In Nigeria, lower income households on average spend less (Adegbulugbe & Akinbami, 1995), with wealthier households allocating 9% more of their total household income to energy consumption (Shittu, et al., 2004).

   The influence of household occupant type has also been demonstrated to play a role in domestic electricity consumption. Households with children use more electricity (O'Doherty, et al., 2008), (Weismann, et al., 2011), (Brounen, et al., 2012) than households without. A positive relationship has been shown to exist between energy consumption and number of adults (Wyatt, 2013). The age and education level of the household head4 (HH) has also been demonstrated to affect household energy consumption. Households with a HH older than 65 have been revealed to use less electricity than households with HH aged between 45 and 64 (Leahy & Lyons, 2010), (Yohanis, et al., 2008), while households with HH aged between 19 and 35 have lower electricity use (McLoughlin, et al., 2012). In Nigeria, the age of the HH has also been determined to influence residential energy use (Shittu, et al., 2004). While the influence of the education level of the HH has been established to be insignificant for energy consumption in Nigeria, it has a stronger relationship with income level which influences household spend on electricity (Shittu, et al., 2004). However, Ogwumike, et al. (2014) explains that education of the HH increases the adoption of electricity as the primary household energy source in Nigeria.

On consideration of the above factors, the occupancy related questions of the survey included the total number of occupants, age range of occupants, number of employed occupants and building type as indicators of household wealth. A weekday and weekend activity summary diary were also included to obtain information on household activity patterns. Information on activity patterns during power supply and power outage was also obtained.

2) Technical factors: Building type and building age have been indicated to have an effect on residential energy use. Higher degrees of building isolation have been established to increase energy use (Wyatt, 2013) (Yohanis, et al., 2008) (Weismann, et al., 2011). Leahy and Lyons (2010) explain that apartments use less energy than semi-detached buildings due to smaller floor area. Semi-detached buildings were also demonstrated to consume less electricity than detached buildings. While Weismann, et al. (2011) and Leahy and Lyons (2010) have shown that older UK buildings (pre-1918) consume more electricity due poor insulation, Chong (2012) demonstrated the opposite, with newer homes (post-1970) using more electricity. Oluseyi, et al. (2016) have revealed an insignificant impact of building age on energy consumption in Nigeria. The number of rooms and floor

[4] The household head is the acknowledged unit head in a household by its other members.

area in the building have been shown to impact electricity consumption. Energy consumed by a building increase with the number of rooms and floor area in that building (Yohanis, et al., 2008) (Leahy & Lyons, 2010) (Wyatt, 2013) (Oluseyi, et al., 2016).

Ownership of electrical appliances has also been established to increase residential electricity consumption (Bedir, et al., 2013) (Leahy & Lyons, 2010). Weather sensitive appliances such as ACs have also been demonstrated to have a significant effect on domestic energy use (Sailor & Pavlova, 2003) (Sanquist, et al., 2012) (Ndiaye & Gabriel, 2011). The use of fans for space cooling has also been determined to be significant in Nigeria (Adegbulugbe & Akinbami, 1995).

Based on the above factors, questions pertaining to the number of rooms and appliance ownership were also included in the survey. The questionnaire used for the survey is presented in the Appendix A.

4.2.2 Survey Description

The face-to-face survey was carried out in Nigeria's federal capital territory, Abuja. Abuja (FCT) was selected for this study due to its diversity and equal distribution of people from all over the country.

Abuja Electricity Distribution Company (AEDC), the DisCo whose customers were surveyed, supplies electricity to Abuja (FCT), and three other states (Figure 4-2).

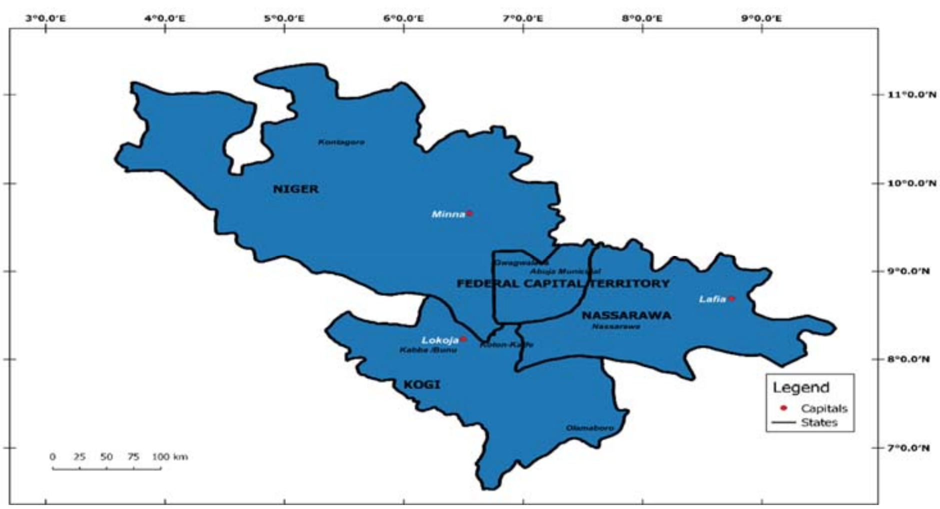


Figure 4-2: States supplied by AEDC

AEDC comprises six regions and twenty-eight business units, with three regions dedicated to Abuja (FCT) and a region dedicated to each of the other states. The survey was administered in FCT North, FCT Central and FCT South. These three regions represent 87% of the total energy allocation within AEDC. These 3 regions also represent 30% of the residential customers within AEDC. The face-to-face questionnaire was distributed with the support of AEDC through its customer service centres in the 3 regions.

Residential customers in Nigeria are categorized according to their tariffs (Table 4-1). R1 customers are the lowest energy consumers. R2 customers consist of customers typically in flats and whole buildings. R3 customers are low voltage maximum demand customers, typically small estates and government houses. R4 customers are maximum demand customers on high voltage connection levels (11/33kV).

Table 4-1: Customer Tariff Class (NERC, 2015)

Tariff Type	Demand kVA
R1	< 5
R2	5 > x < 15
R3	45 > x < 500
R4	500 > x < 20,000

Table 4-2 shows the distribution of customers by tariff class in AEDC and Nigeria as a whole.

Table 4-2: Customer distribution by Tariff Class (%) (NERC, 2015)

Customer Tariff Class	Nigeria	AEDC
R1	2.1	1.16
R2	97.8	98.77
R3	0.09	0.065
R4	0.01	0.005

Two versions of the survey were used: face-to-face and internet based. The sampling methodology recommended by Poduri (2000) was used to determine the sample size. With an assumption of a 5% error margin and 99% confidence interval level, the methodology yielded a target sample size of 750 for the face to face survey. With an adjusted confidence interval level of 95%, and the same error margin, a sample size of

350 online respondents was targeted for the Internet survey. A third of the paper questionnaires (250) were distributed in each of the 3 business regions in Abuja (FCT).

The objective of this study, which is to increase the understanding of residential demand patterns and aid power supply, was explained to respondents to increase their willingness to participate. While customers from different tariff classes might be served by the same supply point transformer, income disparity plays a role in the dominance of customer types in residential areas e.g. R3 and R4 customers, estates in cities usually have their own transformers, R1 customers live in the outskirts of the city in rural areas. While R1 customers constitute ~2% of all customers, customers in this class are typically clustered, served by the same transformer and need to be modelled separately. One of the advantages of distribution through AEDC was being able to directly identify R1 tariff customers who are typically in a lower income class category and would have been expensive to source this data using recruited interviewers for questionnaire distribution, as transport costs to rural areas would have been added to survey costs.

Due to time and location constraints, an online version of the distributed questionnaire was also prepared to gather data from respondents across Nigeria. The data gathered here was used to validate the Abuja (FCT) data. While self-selection bias and coverage can be skewed towards respondents with internet access (United Nations, 2005), the cheaper deployment costs versus a nationwide survey programme makes this option viable. For the face-to face survey, 532 respondents fully completed the questionnaires yielding a response rate of 71%. The online survey had 305 completed questionnaires with a completion rate of 88%.

Table 4-3 provides a breakdown of the respondents in the study. According to the National Bureau of Statistics (2012), the national rural: urban settlement ratio is 65%: 35%, however, this data is not provided at state level. Abuja (FCT) has seen an accelerated development owing to it being the capital of the country, resulting in its rapid urbanisation, with its settlement categorisation ratio departing from the national average.

While income related questions were not captured in the survey due to its perceived invasive nature, urban (54%) and rural (46%) settlements are well represented limiting the risk of wealth bias. The tariff class representation of R1 and R3 respondents is higher compared to AEDC's overall customer base; this is as a result of working with AEDC to ensure representation across all tariff categories. R3 customers represent respondents living in small estates. The occupancy per household figure of 4.35 agrees with the 4.5 recorded by National Bureau of Statistics (2012). The age distribution of household occupants agrees with the national data recorded by the National Population Commission (NPC) and ICF International (2014) except for the category of occupants aged under-9 (14 percentage points less than NPC data), however, NPC does not provide a breakdown by state to explain this difference. The working occupants per household comprises both employed occupants and occupants who attend school, to account for daily occupancy patterns.

Table 4-3: Description of Survey Respondents

Variables	N (%)	mean±sd
Customer Region		
FCT North	174 (33)	
FCT Central	174 (33)	
FCT South	184 (35)	
Settlement Type	**532**	
Rural	224 (46)	
Urban	289 (54)	
Tariff class	**532**	
R1	42 (8)	
R2	445 (83)	
R3	10 (3)	
R4	0 (0)	
Unmetered	35 (7)	
Occupants	**2314**	
Occupants/household		4.35±2.49
Occupant age range/household		
< 9	446 (19)	1.91± 0.97
10-17	558 (24)	2.27±1.31
18-64	1291 (56)	2.44±1.53
65-74	15 (1)	1.07±0.27
75+	4 (0)	1.0±0
Working Occupants	**1810**	
*Working occupants/household		3.40±2.29

4.2.3 Survey Results: Appliance Ownership

Appliance ownership data from the survey is presented by customer tariff class in Table 4-4. Appliance ownership by customer tariff class corresponds to the demand classification shown in Table 4-1. R1 customers, typically rural and low-income customers, have the lowest appliance ownership rates for all appliances, especially for high rated power appliances. R2 customers, typically urban customers, have higher appliance ownership rates than R1 customers. R3 customers, which are typically high income and residential estate customers, have the highest appliance ownership rates.

Table 4-4: Survey electrical appliance ownership by tariff class (%)

Appliance	R1	R2	R3
Fan	88	96	100
Air Conditioner	19	41	100
Refrigerator	38	70	100
Freezer	5	41	70
Fridge-Freezer	10	22	70
Microwave Oven	5	35	100
Kettle	21	43	70
Shower	0	14	40
Electric Cooker	17	27	100
Television	86	93	100
PC	24	50	100
Washing Machine	0.5	31	100
Electric Iron	69	88	80

Table 4-5 shows the ownership of high power rated appliances. Appliance ownership of high power ratings are low compared to that of a developed country such as the UK (Tsagarakis, et al., 2013), but also high compared to the national figures for Nigeria (National Bureau of Statistics, 2016). The low national ownership rates from the published statistics for Nigeria is impacted by the electrification rate of 51.3% in the country. The National Bureau of Statistics (NBS) survey includes unelectrified respondents which will reflect in the low appliance ownership figures, as constant electricity supply influences electrical appliance purchases (McNeil & Letschert, 2010). With a higher electrification rate in Nigeria's urban areas, the appliance ownership is higher than that of the national average. The disparity in ownership rates could also be attributed to the survey location, Abuja (FCT), having higher population wealth indicators compared to the national average (National Bureau of Statistics, 2012). Other home appliance surveys done for Nigeria have shown AC ownership to be about 2% (National Population Commission (NPC) and ICF International, 2014), (Osuorah, et al., 2013), (Adegbulugbe & Akinbami, 1995) which is low compared to the AC ownership rates from the survey.

Based on the ownership (Table 4-4) and usage rates (Table 4-6), it is possible to determine the population of AC owners who actually use it. Usage rates here represent the number of respondents that own and use the appliance.

Table 4-5: High power rated appliance ownership comparison (%) Nigeria vs UK

Appliance	Survey	Nigeria (All)	Nigeria (Urban)	UK
Washing machine	33	1.5	3	93
Electric cooker	26	3.4	5.8	46
Electric shower	31	N/A	N/A	99[5]
Microwave oven	35	3	6	92
Air conditioner	39	2.6	5.1	N/A

The household cooling rate for R1 customers is 9.5%; R2 customers, 18%; and R3 customers, 60%. Reasons for low AC usage rates among the respondents are presented in Table 4-7. It can be seen that current electricity costs are a determining factor for using ACs in Nigeria. 2016 residential tariffs for AEDC are: R1 1cents/kWh, R2 7cents/kWh and R3 14cents/kWh (NERC, 2015). 46% and 33% of R1 and R2 customers, respectively, reported costs as being a deterrent to AC usage. This demonstrates that socio-economic factors might be just as important as weather in determining air condition usage (Sailor & Pavlova, 2003).

Table 4-6: Cooling appliance usage (%)

Appliance usage rate	R1	R2	R3
Fan only	37.5	45.5	30
Air Conditioner & Fan	12.5	9.5	0
Air Conditioner only	37.5	36.5	60
None of the above	12.5	8.5	10

Table 4-7: AC use determinants

Reasons	Frequency (%)
Cost of Electricity	145 (33)
Health	68 (16)
Weather	79 (18)
All of the above	5 (1)
Other	137 (32)

From Table 4-7, the impact of weather on air conditioning usage may be related to seasonal temperature changes. The results of this survey agree with findings in

[5] Shower ownership is 99% in the UK. Households with electric water heating is 48%.

literature on the impact of weather on air conditioning usage in Nigeria (Adaji, et al., 2016).

4.2.4 Survey Results: Household Activity

Respondents were asked to provide the time the presented activities typically occur in their homes on weekdays and weekends. Plots of the daily distribution of household activity occurrence times are presented in Figure 4-3 and Figure 4-4.

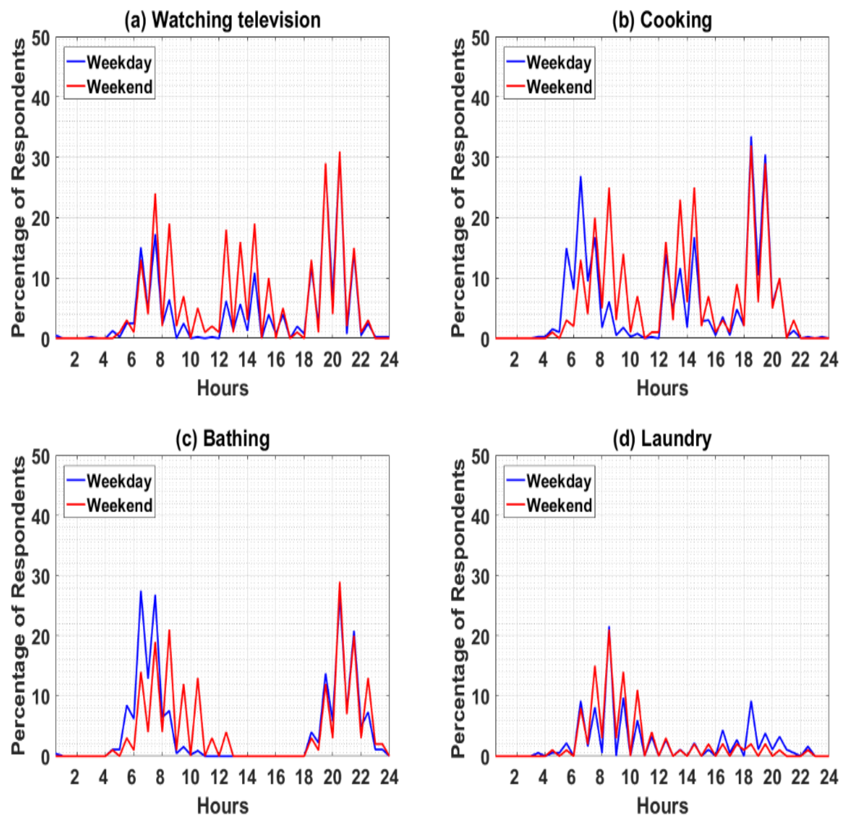


Figure 4-3: Time of Household Activity
(a) Watching Television (b) Cooking (c) Bathing (d) Laundry

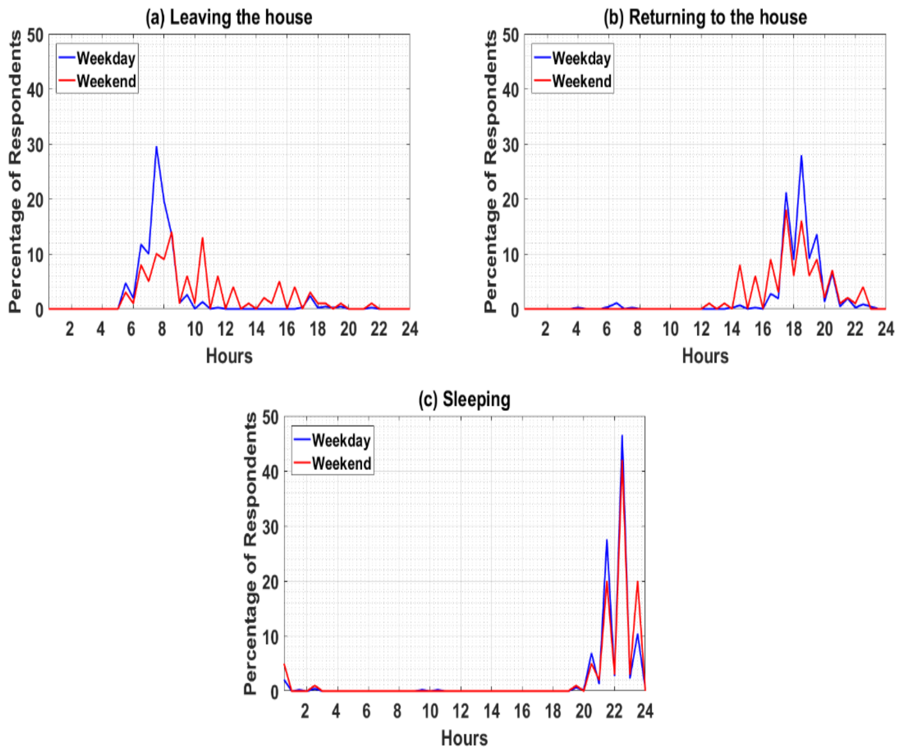


Figure 4-4: Time of Household Activity
(a) Leaving the house (b) Returning to the house (c) Sleeping

Household activities are characterised by patterns of occurrence, with some occurring throughout the day such as watching television, and others occurring around particular periods, such as sleeping. Similar activity patterns between weekday and weekend are observed in Figure 4-3 and Figure 4-4, with the exception of laundry, that sees more weekday evening activity. Bathing, cooking and 'leaving the house' activities occur earlier on weekdays than weekends. The 'watching television', 'leaving the house' and 'returning to the house' activities, have a broader daily distribution during the weekend than during weekday. More respondents also return later to the house during the weekday compared to the weekend. It is observed that respondents spend more time in the house during the weekend compared to the weekday. Differences in weekday type occupancy pattern typically translates to differences in daily energy consumption (Argonne National Laboratory, 2011). Table 4-8 shows the average duration of the sleeping and watching television activities and evidences the day type pattern. The activity results are used to generate the daily household profiles which are converted to electricity demand in the model.

Table 4-8: Average duration of activity (hours)

Activity	Weekday	Weekend
Sleep	6.5	7.4
Watching television	3.7	5.2

Due to the use of a half-hourly activity questionnaire in the survey, there was a tendency for concentration of activities at half-hourly time points, without the finer spread across periods that a higher frequency diary would have produced. The survey aimed to gather data on activity patterns as they would typically occur during periods of uninterrupted power supply. Activities stated to occur between 9:00am and 9:30am, will begin at any time within that time band. A 60-minute moving average treatment was performed on the activity data to smooth out the activity "peak points", providing a window of ± 1 hour during which the activity could actually occur, as shown in Figure 4-5. Appliance sharing is implied and not modelled separately, as the survey result is at household and not individual occupant level. Entertainment, cooking and laundry are typically communal activities in Nigerian households.

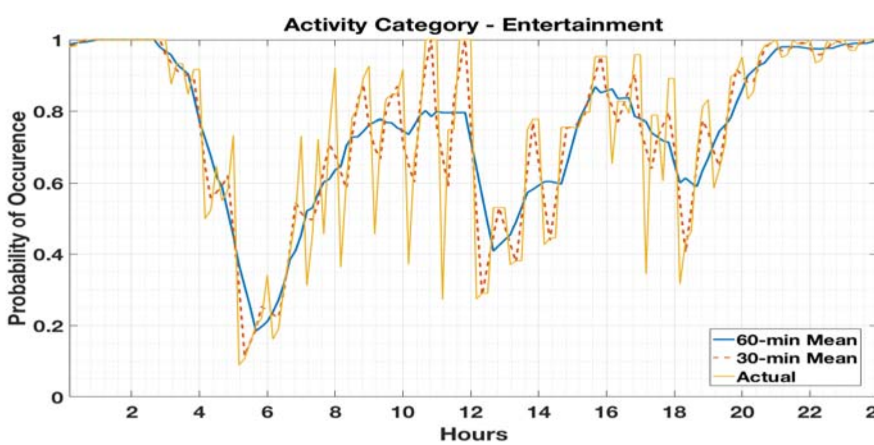


Figure 4-5: Entertainment activity profile

4.2.5 Survey Results: Household Characteristics

Survey results for the breakdown of building stock type by tariff class is presented in Table 4-9. A comparison of energy customers by building type shows that the floor area occupied by lower energy users is smaller than those occupied by higher energy users. 73% of R1 respondents' dwell in single room apartments compared to 43% of R2 respondents. For the other building types with larger floor areas, these are occupied by 27% of R1 respondents, compared to 52% for R2 and 100% for both R3 and R4 respondents.

Table 4-9: Building type of respondents by tariff class (%)

Building Type	R1	R2	R3	R4
Single Room	73	48	0	0
Flat	8	25	30	0
Semi-Detached	11	12	0	0
Detached	8	15	70	100

4.3 Model Input data

A weather sensitive stochastic model capable of simulating residential electricity demand for Nigeria is developed and presented in this section. The model comprises of three main models: socioeconomic, weather and an electricity demand model. The appliance model and the AC model are components of the electricity demand model (Figure 4-1).

The model has been implemented in MATLAB, with simulation time step at a one-minute resolution to capture demand volatility. Socioeconomic profiles which are generated from the survey results and daily weather profiles generated using satellite reanalysis data serve as the model input data. The survey activity data, which was collected at a half hourly resolution, is converted to one-minute resolution to meet the simulation time step requirements of the model. The weather data, which is available at an hourly resolution, is also converted to a one-minute resolution. An overview of the input data is presented below.

4.3.1 Socioeconomic data

Table 4-10 shows the socioeconomic data input. Each household profile generated is assigned data for each field category. The description of the input parameters is presented in this section.

Table 4-10: Socioeconomic data input

Field	Range	Units
Occupants	1 to 5	-
Tariff Class	R1 to R4	-
Building Type	1 to 4	-
Building Location - Longitude	3 to 15	°East
Building Location - Latitude	4 to 13	°North
Building Orientation	-89 to 89	Degrees
Rooms	1 to 3	-
Appliances	1 to 13	-
Thermal Comfort	23.5 to 26.6	°Celsius

i. Occupants: Due to the larger sample size of the NPC and IPF survey, the results in **Error! Reference source not found.** are used to determine the members of each generated household profile. This is used so that each profile generated is statistically representative of a Nigerian household.

ii. Tariff Class: The model generates household profiles within the same tariff class for each simulation, as the power demand of each tariff class are within defined and regulated power bands. This ensures that generated demand profiles do not exceed the power demand allowance of its tariff class.

iii. Building Data: The model assigns a building type to each household profile generated. The allocated building type is dependent on the tariff class.

iv. Building Location: The longitudinal and latitudinal geographic coordinates are assigned to each building to calculate the impact of irradiance on it due to the sun's movement.

v. Building Orientation: In order to capture the thermal response of buildings to external temperature in the cooling model, building orientation of each household has been included in the household profile. The assumption for building orientation assignment is that the wall side that captures the most daily irradiance is facing due south (Wong & Li, 2007). The building orientation assignment is done using the ASHRAE convention, North; 180°, East; -90°, West; 90° and South; 0° (ASHRAE, 2013).Variability in building orientation is included to capture the daily solar irradiance impact. For each building type, each building component in a room e.g. wall, floor, is modelled separately. For the walls, both internal and external walls (active surfaces) are modelled. For single room apartments and flats, they are modelled as externally located in the buildings e.g. apartment blocks, they are part of and only the active surfaces are modelled. The shading effect of buildings is not treated in the model and can be included as part of future work.

vi. Rooms: The number of rooms relates to the number of rooms used for sleeping by the household. Household members are assigned to rooms, with each room having a maximum of two members. This information is important for modelling the cooling demand of households that sleep with air conditioning. Sleeping rooms are assigned to the building types of each customer profile based on the results of the NPC and ICF International (2014) study. Single room apartments are assigned one sleeping room.

vii. Appliances: Electrical appliances, which are dependent on tariff class allocation, are assigned to each household using the survey results shown in Table 4-4. Household demand is influenced by the quantity and power ratings of electrical devices. Households that own and use more high power rated devices will have experience higher peak demand than households with lower power rated devices (ESKOM, 2003). In a recent study it was reported that 41% of 835 sampled households in Nigeria have home businesses (Oseni, 2015). However, that has not been included in the design of this model, as breakdown by business type is not available. Modelling business activity patterns and power demands of business related equipment fall under end-use engineering forecasting for commercial demand and is beyond the scope of this study.

viii. Thermal comfort level: Results of the survey reveal that while the air-conditioner is a weather dependent appliance, there are households that do not use it due to their preferred thermal comfort levels. For this model, the outdoor temperatures are considered to represent the real-life influence on cooling appliance usage frequency and a relationship between indoor and outdoor temperature is used to define household comfort thresholds (Nicol & Humphreys, 2002). Ogbonna & Harris (2008) in a residential thermal comfort study for Nigeria revealed a range of between 23.5°C and 26.6°C, from which values are randomly assigned to households using a uniform distribution.

4.3.2 Weather data

Weather data is required for modelling the electricity demand response of household profiles to changes in ambient conditions. The Nigerian Meteorological Agency (NIMET), provides daily maximum and minimum temperatures, but does not provide daily hourly temperatures. To this end, the Modern-Era Retrospective analysis for Research and Applications, Version 2 (MERRA-2) 2-metre hourly air temperature data has been used to simulate hourly temperature variability. MERRA-2 is the newest multiyear reanalysis produced by the Global Modelling and Assimilation Office (GMAO) of the National Aeronautics and Space Administration (NASA). MERRA-2 is an update of an earlier reanalysis MERRA, which became incapable of assimilating new satellite information (Bosilovich, et al., 2015). This current version is able to ingest data from microwave sounders and infrared radiance sensors, and has also been established that it is substantially better at simulating climate conditions than the older MERRA version (Molod, et al., 2015), (Wargan & Lawrence, 2016).

The reanalysis data is generated at a 0.635° x 0.5° longitude- latitude resolution, grid with an approximate resolution of 50kmx50km. Variables are provided on a vertical grid with 72 layers or interpolated to 42 standard pressure levels. In this work, the 2-dimension single-level full horizontal resolution hourly data has been used. Model weather inputs are based on 2014 MERRA-2 data.

For irradiance, the MERRA-2 surface incoming shortwave flux or global horizontal irradiance (GHI W/m^2) (SWGDN) data has been recommended for hourly solar PV modelling (Richardson & Andrews, 2014) and is the selected re-analysis data type.

4.3.3 Ambient condition simulation

The hourly temperature and irradiance data are used to simulate the ambient conditions at each building location. The simulation methodology has been implemented using (ASHRAE, 2013). For each day (d) of the year in the simulation, and for each hour (t) of the day, the locational longitude is used to calculate the apparent solar time (AST) using:

$$AST_{d,t} = LST_{d,t} + \frac{ET}{60} + (LON - LSM)/15 \quad (4.1)$$

where *LS*T is the local standard time, *ET* is the equation of time, LON is the locational longitude and *LSM* is the longitude of local standard time meridian. Similarly, the locational latitude is used to calculate the solar altitude β and azimuth ϕ using:

$$\sin \beta_{d,t} = \cos LAT \cos \delta_d \cos H_{d,t} + \sin LAT \sin \delta_d \quad (4.2)$$

$$\sin \phi_{d,t} = \sin H_{d,t} \cos \delta_d \,/ \cos \beta_{d,t} \quad (4.3)$$

where *LAT* is the locational latitude, δ is the daily solar declination and *H* is the daily hour angle which measures the angular eastward or westward longitudinal displacement of the sun. The position of the sun at any time has 2 components, the altitude and azimuth. The solar altitude is the position above the horizontal, and for the solar azimuth, its position is measured from the true south of a compass. Each wall in a building is at an angle to the true south of a compass, and its orientation (azimuth) is the compass direction it faces. For vertical surfaces (such as walls), the angle of incidence of the sun's rays is dependent on the angular difference between the solar azimuth and surface azimuth, and the solar altitude. It can be expressed as

$$\cos \theta = \cos \beta \cos(\phi - \psi) \quad (4.4)$$

where θ is the incidence angle on the wall in degrees, β is the solar altitude in degrees, ϕ is the solar azimuth in degrees and ψ is the wall azimuth in degrees. The incidence angle determines the intensity of solar irradiance on a wall's surface.

The GHI and the MERRA-2 extra-terrestrial radiant flux (SWTDN) data are used to estimate the direct and diffuse irradiance at each building location. The direct irradiance, the irradiance component measured perpendicularly to sunrays, and the diffuse irradiance, the irradiance component measured on the horizontal surface are deduced by estimating the diffuse fraction *d*. This can be defined as

$$d = \frac{E_d}{E_b} \tag{4.5}$$

where E_d is the diffuse horizontal irradiance (W/m^2) and E_b is the beam normal irradiance (W/m^2).

The Boland-Ridley-Lauret (BRL) methodology (Ridley & Lauret, 2010), recommended for its statistical predictive strengths over comparable models and ease of application (Torres, et al., 2010), has been adopted for the diffuse fraction estimation. The direct and diffuse irradiance components are then used to calculate the incident irradiance on the external building components i.e. wall and windows.

The beam, diffuse and ground reflected components of irradiance on a vertical receiving surface are given as:

$$E_{beam,t} = E_{b,t} \cos\theta \tag{4.6}$$

$$E_{diffuse,t} = E_{d,t} L \tag{4.7}$$

$$E_{ground,t} = (E_{b,t} \sin\beta + E_{d,t})\rho_g \frac{1 - \cos\gamma}{2} \tag{4.8}$$

$$E_t = E_{beam,t} + E_{diffuse,t} + E_{ground,t} \tag{4.9}$$

where E_t is the total surface irradiance (W/m^2) at hour t, $E_{beam,t}$ is the beam component of irradiance (W/m^2), θ is the angle of incidence in degrees, $E_{diffuse,t}$ is the diffuse component of irradiance (W/m^2), L is the ratio of clear-sky diffuse irradiance between vertical and horizontal surfaces, $E_{ground,t}$ is the ground reflected irradiance component (W/m^2), ρ is ground reflectance and γ is the surface tilt angle in degrees.

The impact of incident solar radiation, radiant exchange with sky and external surroundings on external air temperature is known as the sol-air temperature. The effect of incident radiation on building vertical surfaces impacts the temperature of external air flowing into the building fabric (ASHRAE, 2013). This is calculated as:

$$t_{S,t} = t_{E,t} + \frac{\alpha E_t}{h_O} \tag{4.10}$$

where t_S is the sol-air temperature at time t, t_E is the external temperature at time t, E_t is the total irradiance on the surface, α is the absorbance of surface for solar radiation and h_O is the coefficient of heat transfer by long wave radiation and convection at the outer surface (W/m^2). Based on prior work on building modelling in Nigeria, an assumption has been made of light coloured walls for the buildings, yielding 0.026 as the ratio of absorbance to heat transfer coefficient (Lawal & Ojo, 2011). The sol-air temperature is used to model the daily external temperature conditions at the building fabric.

4.4 Electrical Demand Model

This section presents the operation of the electrical demand model in simulating appliance usage and its conversion to electrical power demand. The description of the AC model and operation are presented in section 4.5.

4.4.1 Household Activity Profiles

Daily occupancy profiles of each household are constructed in the model based on results of the survey. These profiles simulate the active presence of occupants in the building. Various methods have been implemented in simulating domestic activity profiles including, Hidden Markov Models (Jenkins, et al., 2014), Markov Chains, (Widen & Wackelgard, 2010), Probabilistic models (Capasso, et al., 1994), (Paatero & Lund, 2005), Monte Carlo Markov Chains (Richardson & Infield, 2008), (Collin, et al., 2014).

In this model, household profiles are simulated using a combined probabilistic and Markov Chain approach. The half-hourly time resolution of the survey limits the detailed capture of transitions between household activities. While this transitional information can be gathered from the results, the data performance does not allow the generation of smooth activity transitions as implemented by Colin, et al. (2014), which is obtained from the TUS data of the UK capturing 25,000 households at a 10-minute resolution. The UK TUS data captures the changes from one activity to another at a high resolution e.g. A household occupant could be “watching TV” at 10:00 am, and then “switching on the kettle” at 10:10am. A similar level of detail in transitions is not obtainable using a half-hourly diary. The approach used here is influenced by

Richardson and Infield (2008), whereby transitions are obtained between active and inactive states to replicate household activity, and then simulating the probable activities the household could be involved in.

The survey provides data at the household level but not at the individual household member level. However, for each household activity in the model, it is feasible to assign active household members based on the number of occupants present in the house. The questionnaire did not include questions on public holidays, therefore activities in this study relate to typical weekdays and weekends only.

Active states are defined as periods when the household is functional and engages in activities that require electricity, while inactive states are periods the household is asleep or does not engage in such activities. Although the model generates cooling demand from air conditioning and fans while the household is present and asleep, the household is classified as inactive during those periods.

From a time of use diary, the Markov Chain transitional probability matrix can be developed by calculating all transitions between active (x) and inactive (y) states using (Richardson & Infield, 2008):

$$p_{xy}(\tau) = \frac{\sum n_{xy}}{n_x(\tau)} \tag{4.11}$$

where $p_{xy}(\tau)$ is the transition probability from state x to y between two consecutive time intervals, τ and $\tau + 1$, n_{xy} is the number of transitions from state x to y between τ and $\tau + 1$, and $n_x(\tau)$ is the population in state x at time τ. This is applied to the household survey diary to generate the transitional probability matrix and probability of initial conditions across all the households. The probability distribution of the household initial condition is determined by the activity state at $\tau(1)$.

In simulating activity in the model, transition occurs at each time step τ by comparing the probability p_{xy} to a generated random number, to determine the household active state, $hh_{state} \in [0,1]$. The types of household activities simulated in the model are shown in Table 4-11. The electrical appliance ownership in typical Nigerian households has influenced this categorisation. An activity such as dishwashing is done manually, as the ownership rate of dishwashers is negligible and therefore not included in the categorisation. The results of the survey were used to develop a probability distribution of household activity types by weekday type.

For each activity category, profiles are generated that determine the likelihood of occurrence of that activity at any time of the day, that is, the probability of that activities' occurrence across all active households at that time.

Table 4-11: Household activity categories

ID	Activity type	Appliance
1	Sleeping	A/C, Fan
2	Entertainment	TV, Radio, PC
3	Cooking	Electric Cooker, Microwave, Kettle
4	Bathing	Electric Shower
5	Laundry	Washing Machine, Electric Iron
6	Leaving the House	N/A
7	Returning to the House	N/A

The survey results include activity records by weekday and weekend. Probabilities are obtained by,

$$p_{j,wd}(\tau) = \frac{\sum_{wd=1}^{2} n_{j,wd}}{n_{wd,active}(\tau)} \tag{4.12}$$

where $p_{j,wd}(\tau)$ is the probability of occurrence of activity type j on the weekday type at time (τ); $n_{j,wd}(\tau)$ is the total number of households performing that activity at time (τ); and $n_{wd,active}$is the total number of households that are active at time (τ).

With the household active state known, the number of occupants performing an activity is then simulated at each time step. While transition states between household occupants cannot be deduced from the survey results, the activity profiles "leaving the house" and "getting home" enable the simulation of the independent movement of household members. The model is able to layer household active states with occupant movements. This can be determined by

$$n(i,t) = n - \sum_{t=1}^{t_{leave}} q(i,t) + \sum_{t_{leave}}^{1440} w(i,t) \tag{4.13}$$

$$q(i,t) = \begin{cases} 1, & r \leq p_{leave}(i,t) \\ 0, & r > p_{leave}(i,t) \end{cases} \tag{4.14}$$

$$w(i,t) = \begin{cases} 1, & r \leq p_{return}(i,t) \\ 0, & r > p_{return}(i,t) \end{cases} \quad (4.15)$$

where n is the number of occupants in household profile i at time t in minutes, r is a generated random number, q represents any occupant leaving the house, w represents any occupant returning to the house, t_{leave} is the time the last occupant leaves the house, p_{leave} is the probability a household occupants leave the house at t, and p_{return} is the probability a household occupant returns to the house.

Figure 4-6 displays the active states and movements of a 5-person household. The occupancy changes from 5 to 4 when Occupant 1 leaves the house at 6.20am, and then from 4 to 3 when Occupant 2 leaves at 10.30am. The occupancy changes to 4 at 6.20pm and then to 5 at 6.50pm when the last household occupant returns.

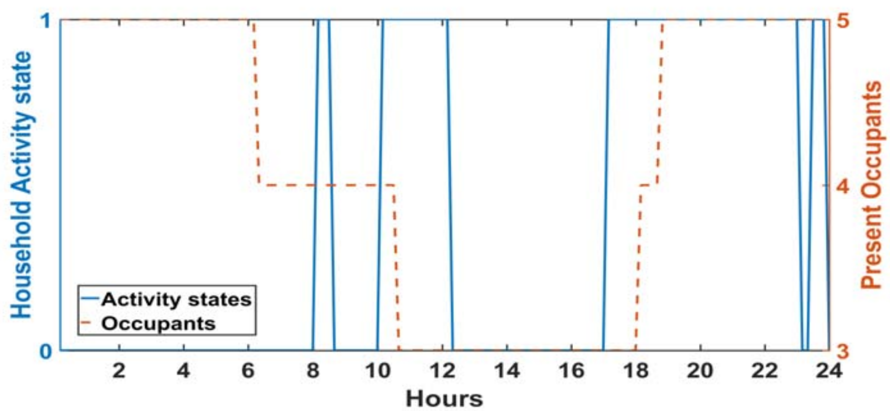


Figure 4-6: Household occupant activity states

4.4.2 Appliance Model

A list of available electrical appliances in Nigeria along with their power ratings is available from Community Research and Development Centre (2009) and light bulb ownership rates by type and rating is available from the United Nations Development Programme (UNDP), Energy Commission of Energy (ECN), Federal Ministry of Environment, Global Environment Facility (2013). Annual energy consumption by appliance type, along with the frequency of use of certain appliances is also available from the UNDP report. Power ratings of typical UK residential electrical equipment are provided by Tsagarakis, et al. (2013). The activity profiles have been converted to a one-minute resolution to capture detailed appliance energy use. The appliances have been grouped according to one of the seven household activities defined e.g. iron and washing machine linked to laundry activity (Table 4-11).

Each household is populated with appliances using the socioeconomic model. Appliance power ratings are determined within a uniform set of values from a list of similar appliance types available in Nigeria (Community Research and Development Centre, 2009). During each simulation, the activation of each human-dependent appliance is determined by the active states generated for that household. For appliances independent of human intervention, these are simulated based on pre-set duty cycles e.g. washing machines.

During a simulation run, each appliance linked to an activity category will be activated based on the probability profiles of that activity at that time step. For example, based on the probability of households watching television at 6pm, the television and satellite box could both be switched on. This allows multiple appliances to be used simultaneously. These household activity profiles are weekday type dependent, as household patterns vary on weekdays and weekends.

A scaling factor to regulate the annual energy use of certain appliances has been introduced into the model. The measured annual energy use of some appliances in Nigeria for each of 6 states served by different DisCos is available in the UNDP report. The scaling factor is a measure of the probability of the daily activation of an appliance based on its annual use. The scaling factor calibrates the activation of appliances within the model, to simulate the typical usage of that appliance for a state being analysed based on results of a small measurement campaign. The scaling factor can be expressed as (Richardson, et al., 2010)

$$s_{j,E} = \frac{f_{j,E}(\tau)}{T - \tau} \tag{4.16}$$

where $s_{j,E}$ is the scaling factor, $f_{j,E}(\tau)$ is the total number of cycles required to consume energy E (kWh) for appliance j. τ is the total operating time of appliance j in a year expressed in minutes, and T is the total time in the year expressed in minutes. Using the derived scaling factor of the appliance energy consumption for the states, the model is calibrated for the same appliance to simulate actual energy use patterns.

The household active state is converted to electrical energy demand using the power ratings of appliances, activity profiles, appliance scaling factor and duration of appliance use. For a household that owns an appliance, the demand of that appliance is determined by its current active state at time t, the activity probability linked to that appliance at t, the appliance active demand or stand-by active demand and the duration of appliance use. For appliances that do not depend on human activation, rather than the household current active state, they depend on pre-configured duty cycles. The appliance power demand is simulated at a 1-min resolution.

Together, the appliance activation probability, the product of the household active state and the activity probability, determines the probability that an appliance will be switched on if a household performs that activity. Appliance activation occurs if a generated random number is less than the product of the appliance activation probability and the appliance scaling factor during the appliance activation period.

This can be expressed as

$$p_{j,a}(t) = p_j(t) \times hh_{state}(t) \tag{4.17}$$

$$D_a(t) = \begin{cases} R, & r < p_{j,a}(t) \times s_{j,E} \\ 0, & r > p_{j,a}(t) \times s_{j,E} \end{cases} \tag{4.18}$$

where $p_{j,a}$ is the appliance activation probability at time t of appliance a associated with activity j, p_j is the activity probability and hh_{state} is the household active state. D_a is the electrical demand of appliance a (W), R is the assigned appliance power rating (W), $s_{j,E}$ is the scaling factor of appliance a, and r is a generated random number.

The duration of appliance usage is determined from the survey results for human dependent appliances and appliance duty cycle studies for other appliances (Tsagarakis, et al., 2013).

Lighting demand has been modelled using an adaptation of the code developed by Richardson, et al. (2009) and hourly irradiance data generated from the weather model. The model uses a combination of the household activity profile, effective occupancy, irradiance, lighting unit frequency use and random duration periods. The number of lighting units are randomly selected for each household and each unit is assigned a frequency use. Lighting remains activated if the household is active and the irradiance goes below a threshold level. The lighting use is also determined by the occupancy levels, with energy usage increasing with the number of household occupants.

Figure 4-7 shows the conversion of a household active state to an electric cooker power demand for cooking events. The power rating of the cooker is 3kW, which was selected from a uniform distribution between [2.5, 3.5] kW (Community Research and Development Centre, 2009). The household is active during the three periods highlighted in blue. The regions highlighted in yellow show the appliance activation period, i.e., when the electric cooker could be activated. To simulate cooking, the random number test then determines appliance activation, and as is shown below, cooking occurs in the afternoon and in the evening. For each cooking activity, the duration is selected from a uniform distribution between [15.0, 30.0] min from the duration of cooking obtained from the survey.

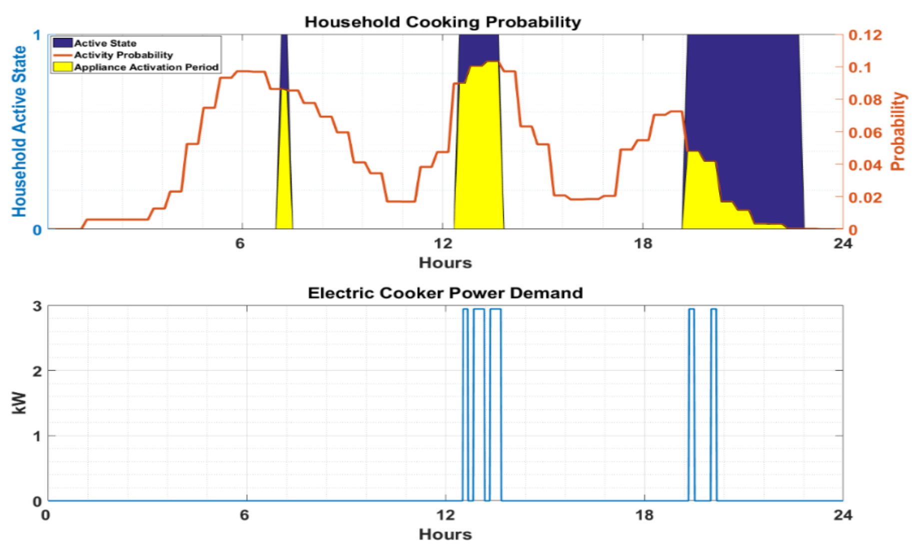


Figure 4-7: Conversion of Household Active State to Electrical Demand

The total household active power demand, D_{hh} , are the sum of demand from all the household appliances A expressed as

$$D_{hh}(t) = \sum_{a=1}^{A} D_a(t) \tag{4.19}$$

where D_a is the active power demand (W) of appliance a at time t.

The model demand output by appliance type for a single 3-bedroom household is shown in Figure 4-8 (note that demand levels vary). The cold load demand demonstrates the cyclical patterns of typical cold loads i.e. fridge and freezer. Lighting demand is activated for a short period in the morning and longer period in the evening typical of Nigerian homes. The fan demand is also shown, with 0.6kW during the night, representing the aggregate demand from three bedrooms during sleeping hours, and 0.2kW at different periods of the day from the living room.

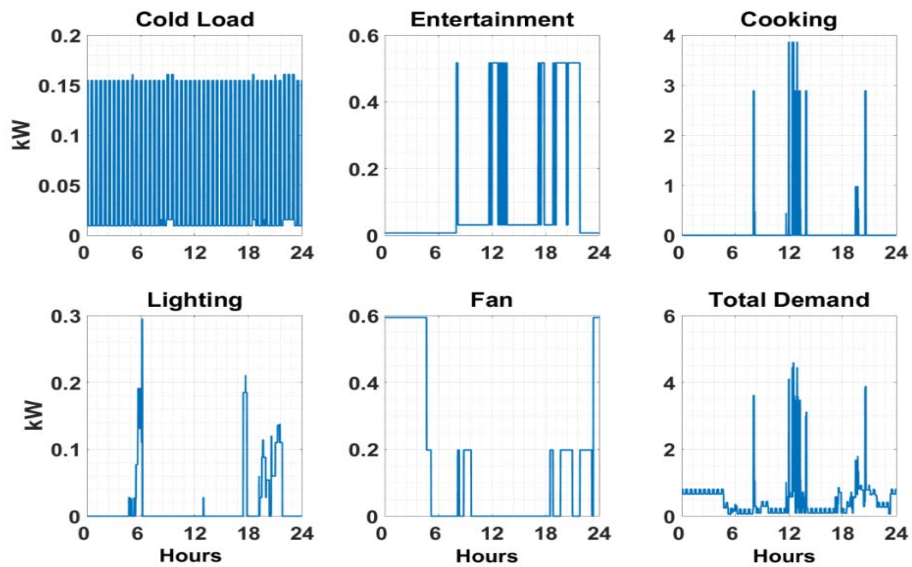


Figure 4-8: Single Household Electricity Demand

4.5 Air Conditioner Model

A cooling load simulation model has been developed as part of the household energy model to estimate cooling energy demand. The aim of this model is to simulate the cooling energy demand of a typical Nigerian residential building coupled with reasonable assumptions to generate load profiles. The cooling model has been implemented as a multi-zone model with the cooling load requirements of each room or zone calculated separately as described in Jones (2001) and ASHRAE (2013). This allows the activity states and present occupancy data to determine occupant heat gains and the activation of cooling demand in the different rooms modelled as part of the building.

The change in temperature across the building fabric, which occurs via the heat transfer mechanisms of conduction and radiation, is a slow process, taking place over a period of hours. Heat flow through the building fabric, the wall, door and windows, is due to the temperature difference outside the building and within the building, and the heat storage capacity of the building (Crabb, et al., 1987). This fabric or conductive heat gain can be represented by

$$q_b = k\Delta\theta \tag{4.20}$$

where q_b is rate of heat gain (W), k (W/ K) is the product of thermal transmittance (W/m^{2}K) of the building fabric and its area (m^2) and $\Delta\theta$ is the temperature difference between the internal and external environments (°C). The external air temperature includes the effect of solar irradiance, and this is referred to as the sol-air temperature.

Infiltration heat gain, which is the inward flow of warm air into the building, can cause a rise in temperature requiring the air to be cooled. This can be represented by

$$q_i = 0.33NV\Delta\theta \tag{4.21}$$

where q_i is the rate of infiltration heat gain (W), N is the air change rate per hour (h^{-1}), V is the volume of the room (m^3) and $\Delta\theta$ is the temperature difference between the internal and external environments (°C).

Heat gain via fenestration is calculated from the conductive heat gain through glass and solar gain through glass using

$$q_{w,tot} = q_{w,f} + q_{w,solar} \tag{4.22}$$

$$q_{w,solar} = A_w q_{w,c} sf \tag{4.23}$$

where $q_{w,tot}$ is the total heat gain from the window (W), $q_{w,f}$ is the window conductive heat gain (W), $q_{w,solar}$ is the solar gain through glass (W), A_w is the area of the window (m^2), $q_{w,c}$ is the cooling load from solar heat gain (W) and sf is the window shading factor.

Heat gains from occupants vary based on the level of activity they are involved in. A resting human emits 72 W, which can rise to 396 W if involved in a strenuous activity (Ohajianya, et al., 2014). Different household equipment emits varying levels of energy based on size and use, for example an emission of 60W from a typical incandescent light bulb. The heat balance within the building determines the thermal comfort of building occupants. In an air-conditioned room, the heat balance is the sum of the heat loss (cooling) from the AC and heat gains in the room. The change in air temperature due to the heat balance is expressed below

$$C_{air}\frac{dT_i}{dt} = q_{gains} - q_{AC} \tag{4.24}$$

where C_{air} is the specific heat capacity of air within the room (J/K), q_{AC} is the heat outflow from the air-conditioner and q_{gains} are the heat gains within the room (W). An airflow rate of 6m^3/min as recommended by ASHRAE (2015) has been used in the model, with an assumption of 0.5 room air changes per hour (ACH) due to natural infiltration. A cooling capacity of 2.6kW, with an Energy Efficiency Ratio (EER) of 9.47Btu/hW has been used in this model.

4.5.1 Building Modelling

Standards for buildings in Nigeria are outlined in Federal Ministry of Housing and Urban Development Nigeria (2006). The thermal and mechanical properties of typical materials used in the building industry in Nigeria are defined by Wenapere and Ephraim (2009), Lawal and Ojo (2009), Kamiyo, et al., (2011) and Batagarawa (2012).

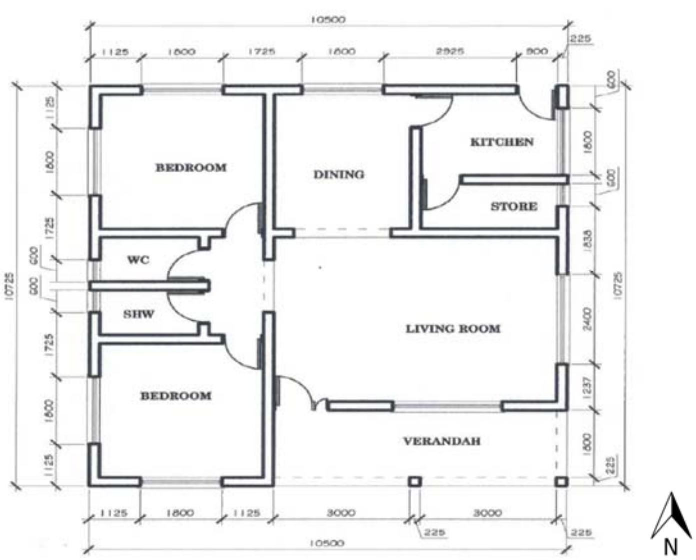


Figure 4-9: Model Building design (Atolagbe, 2013)

To facilitate more credible modelling of AC use, 4 building types are considered, with buildings are divided into two zones: bedrooms and living rooms. Single room apartments, which are typical of high density residential areas in Nigeria, usually have just one window and one door. The other building types used in the model, which are representative of medium and low-density residential areas, have been designed in the model as shown in Figure 4-9.

The thermo-physical properties of building materials used in the model are displayed in Table 4-12 (McMullan, 2007), (ASHRAE, 2013).

Table 4-12: Thermo-physical properties of building structure

Component	Material	Width (m)	Thermal Resistance (m^2 K/W)
Wall	Sandcrete block	0.225	0.234
	Internal and External Plaster	0.015	0.083
	Cavity	-	0.180
	Internal surface	-	0.120
	External surface	-	0.060
Floor	Ground	0.150	0.227
	Other	0.150	0.133
Roof	Concrete	0.150	0.133
Windows	Single glazing	-	0.18
Doors	Flush (solid core)	0.230	0.441

For walls, sandcrete blocks have been selected for the model; these are extensively used in the building industry in Nigeria. They are hollowed blocks, with one-third of a typical block volume, and a density of 1,947kg/m^3 (Wenapere & Ephraim, 2009). The specific heat capacity of the concrete used in the model is 800J/kg K, while that of sandcrete is 880J/kg K (ASHRAE, 2013). A wall to window ratio of 24% has been used for external walls. Single-glazed windows, typical of Nigerian homes, and usually fitted with mosquito nets, have been assigned an internal shading factor of 0.8.

The heat gain across each building fabric component in the room is modelled separately and combined to calculate the room heat gain. An example is shown using a graphical representation of the heat gain across an external wall, created using Simulink and presented in Figure 4-10. The blocks represent the wall fabric and temperature input.

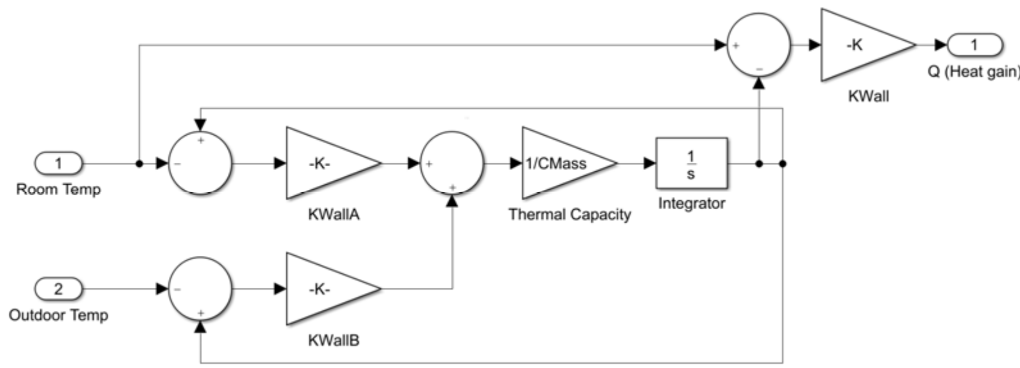


Figure 4-10: Heat gain across external wall

The thermal response of the building fabric due to its mass can be expressed by (Crabb, et al., 1987)

$$C_{mass}\frac{dT_{mass}}{dt} = -k_{WallB}(T_{Wall} - T_{out}) - k_{WallA}(T_{Wall} - T_{room}) \qquad (4.25)$$

where C_{mass} is the thermal capacity of the building (J/K), T_{room} is the room temperature (°C), T_{out} is the external temperature (°C), T_{Wall} is the temperature of the building mass (°C), k_{WallA} represents the thermal conductance of heat flow from within the building to the building fabric and k_{WallB} represents the thermal conductance of heat flow from the building fabric to the external environment (W/mK).

The indoor temperature is defined by the AC operation, and the start point temperature is based on results of a household indoor temperature measurement campaign across the country (United Nations Development Programme, Energy Commission of Nigeria, Federal Ministry of Environment, Global Environment Facility, 2013). Calculated sol-air temperatures are used for hourly external temperatures.

This cooling model focuses on the sensible component, dealing with the changes in the dry bulb temperature i.e., air temperature, of the room. The latent component, involving humidifying and dehumidifying of air, measured by the wet bulb temperature is not factored, as a constant air density has been assumed for all buildings, independent of changes to temperature and humidity. When factored, the latent heat component is about 7% of total cooling load (Jones, 2001). Hence, the model focuses on the heat balance of total sensible heat gain.

4.5.2 Air Conditioner Operation

The cooling model has been designed to simulate the usage of ACs in typical Nigerian homes. Central residential air conditioning systems are not common, with most homes fitted with individual wall or window units in the building zone to be cooled.

The cooling model operates during two time periods, the night time sleep period and the day time active period. The household survey included questions on cooling appliance use during sleeping, the time of going to bed (sleep time), and typical sleep durations on weekdays and weekends. Using the household active profile model, the wake up and sleep time of the household for each day in the model is simulated. Overnight cooling demand is obtained using the wakeup time of the day being simulated and the sleep time of the previous day. For daytime periods, the cooling demand is estimated only for periods when the household is active.

Households are assigned ownership of either fans or ACs. The small percentage of respondents using both appliances for cooling did not justify a dual household cooling system. The fan power rating, sleep duration, number of rooms, and duration of daily household active periods determine the household cooling demand from fans.

For night-time cycles, the air-conditioner is activated at sleep times and operates till the wake-up time. For the daytime cycle, the air-conditioner is activated when the household is active and for the duration of that active period and switched off otherwise. To account for the operation of the AC unit, Equation 4.25 can be rewritten as:

$$C_{air}\frac{dT_i}{dt} = q_{gains} - wq_{AC} \tag{4.26}$$

where w is the thermostat status (either on or off). The state of thermostat operation is governed by (Ihara & Schweppe, 1981)

$$w = \begin{cases} 0, & T_{room} \leq T_s - \Delta \\ 1, & T_{room} \geq T_s + \Delta \end{cases} \tag{4.27}$$

where T_s is the set point temperature (°C) and Δ is the thermostat deadband. This operation activates the AC to switch on when the room temperature goes above the set point and to switch off when room temperature goes below the set point.

The number of present occupants determines the heat gain from occupants. A graphical representation of the AC operation in a room is shown using SIMULINK, where Figure 4-10 shows the AC model, while the total heat gain from across the room building fabric and room occupants is shown in Figure 4-12.

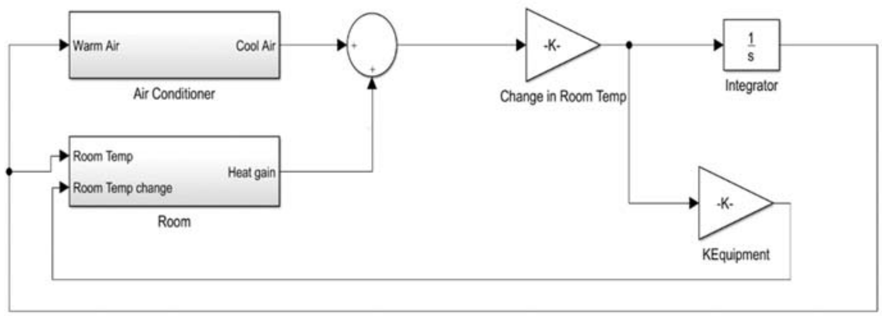


Figure 4-11: Air conditioner model

The heat gain blocks in Figure 4-12 represent the heat gain across the building fabric shown in Figure 4-11. The heat gain across each room building component is estimated separately and then combined to obtain the total heat gain. The change in air temperature is obtained from the addition of the cool air from the AC to the heat produced in the room.

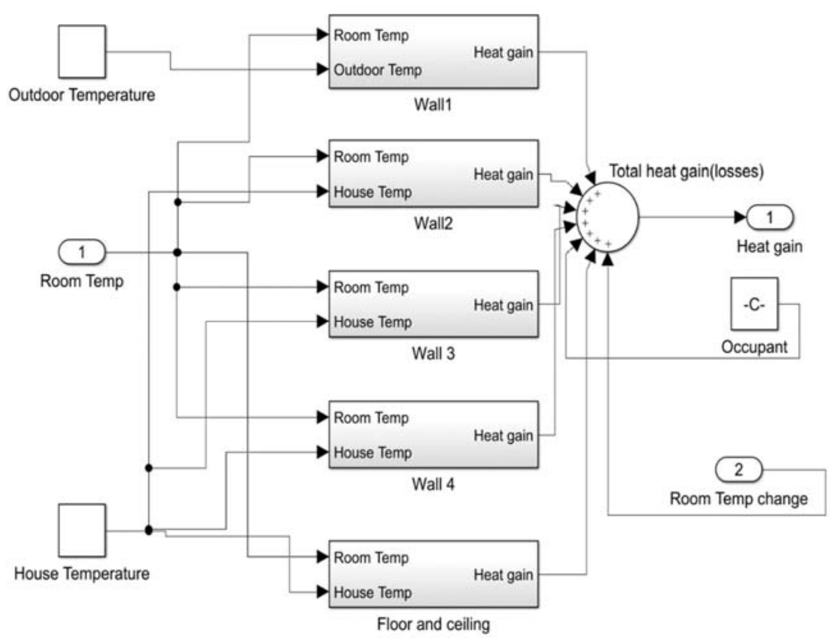


Figure 4-12: Room heat balance

The AC power demand D_{AC} is then obtained using:

$$D_{AC} = wq_{AC}/EER \tag{4.28}$$

4.6 Model Performance

In order to represent energy consumption in Nigeria, the model is used to simulate demand based on tariff class. Household profiles are generated within the same tariff class for each simulation run. Figure 4-13 shows the average hourly demand profile by tariff class. Simulation results are presented for 1,000 household profiles, as no significant change was observed in the output data for larger simulation sets.

The influence on appliance ownership is demonstrated by the magnitude and shapes of the demand profiles of the three tariff classes. An individual R3 customer tariff class represents the demand of a small estate. The demand profile presented is the simulated demand profile of a customer within that estate. All three profiles have morning and evening peaks, representative of typical residential demand profiles, however, the peaks are only prominent in the demand profiles for the R2 and R3 classes who typically own more electrical appliances and demand more energy than R1 customers.

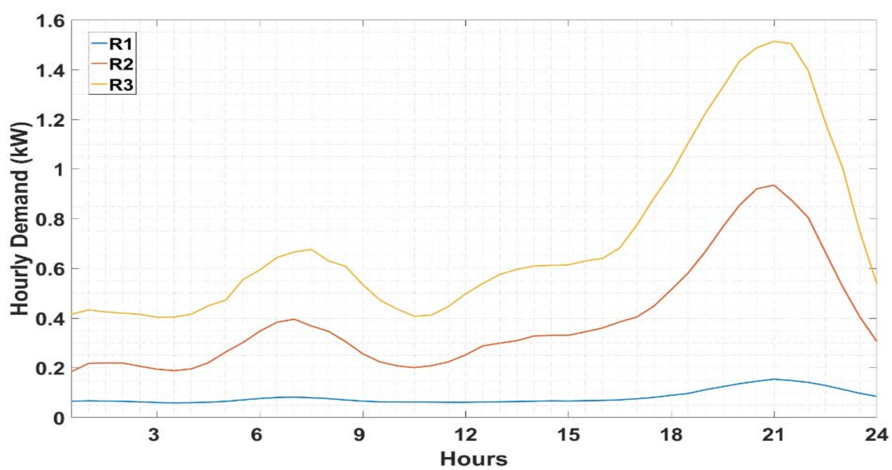


Figure 4-13: Hourly demand profile by Tariff class

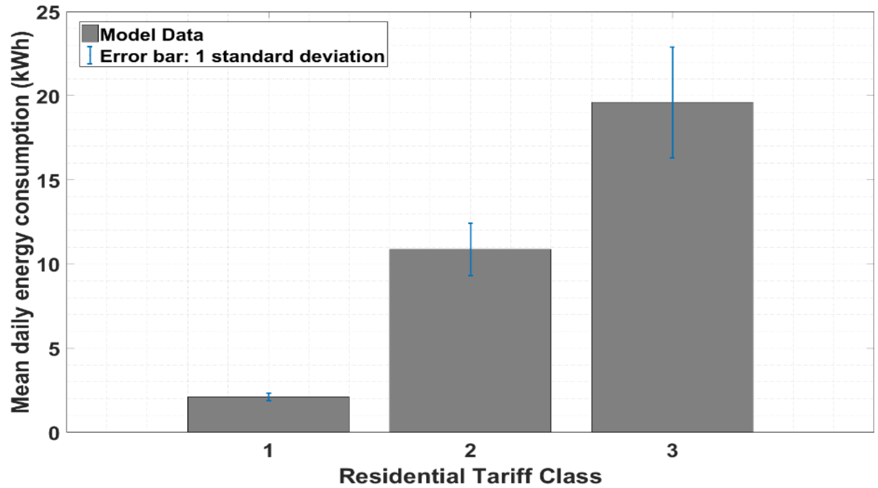


Figure 4-14: Mean daily energy consumption by Tariff Class

Figure 4-14 shows the mean daily energy consumption by tariff class. The markers show the standard deviation either side of the mean and represent the range in which the demand occurs and increases with an increase in appliance ownership. The difference in appliance ownership is the key driver of energy consumption disparity among the tariff classes. The aggregate mean (± standard deviation) daily energy use reveals R3 customers with the highest appliance ownership are the highest daily consumers of energy at 19.6 (± 3.3) kWh. R1 customers consume the least at 2.1 (± 0.2) kWh, with R2 customers in between both, at 10.8 (± 1.6) kWh. Other factors such as floor area also contribute to this disparity, as R2 and R3 customers typically occupy more building floor area than R1 customers and require more energy for cooling demand. Based on the magnitude of the daily energy consumption, the tariff classes reflect the socioeconomic parameters used to define the model input. Subsequent model analysis presented below is based on R2 tariff class customers, who contribute to over 95% of the residential demand in Nigeria (Power Holding Company of Nigeria, 2009).

4.6.1 Cooling Demand

Cooling is activated when the external temperature exceeds the thermal comfort level, either when the household is asleep for night cooling or active for day cooling. Figure 4-15 shows the cooling demand on the same day for a 3-bedroom household with 5 occupants, with a thermal comfort level of 27°C. In this example, the AC is only activated after 8am which is the point the room temperature exceeds the thermal comfort level. The external temperature exceeds the thermal comfort level for 16 hours of the day. During the day, the living room AC unit (day cooling demand) is activated in the morning, in the afternoon - between 12pm and 3pm, at night – between 6.30pm and 11pm and then switched off. For the night hours, the 3 room AC units (3 × 745W) are activated at 11pm. The AC activation is determined by the household active state.

The impact of thermal comfort level on cooling demand for a typical day in Abuja FCT is shown in Figure 4-16. It represents the aggregate mean cooling demand for 1000 profiles with ACs. All households were assigned the same temperature for each comfort level analysed. The error bar denotes one standard deviation of the mean, capturing the influence of the household occupancy pattern on energy consumption. The aggregate mean (± standard deviation) daily energy pattern shows a progressive reduction in energy consumption with increasing thermal comfort levels, with the highest consumption by profiles with a comfort level of 24 °C at 5.8 (± 2.5) kWh, and the lowest consumption in profiles with a comfort level of 32°C at 0.7 (± 0.6) kWh. The comfort level used in this model is based on a Nigerian residential survey of preferred thermal comfort temperature. However, results of indoor measurement campaigns by Amasuomo and Amasuomo (2016) reveal temperatures of between 29°C and 32°C in the south of the country, while those of Adaji, et al. (2016) reveal higher temperatures of between 31.8°C to 36.8°C in the north of the country. A majority of respondents found these thermal levels unacceptable, however their desire for increased air conditioning especially during the dry season is constrained by power cuts and the costs of self-generation (Adaji, et al., 2016). Since the aim of this work is to simulate uninterrupted residential energy consumption in Nigeria, the thermal comfort range selected for this model is deemed sufficient to represent thermal comfort choices in a constant power supply environment. For location specific studies, the thermal comfort levels can be adjusted to capture patterns of actual cooling demand within a network.

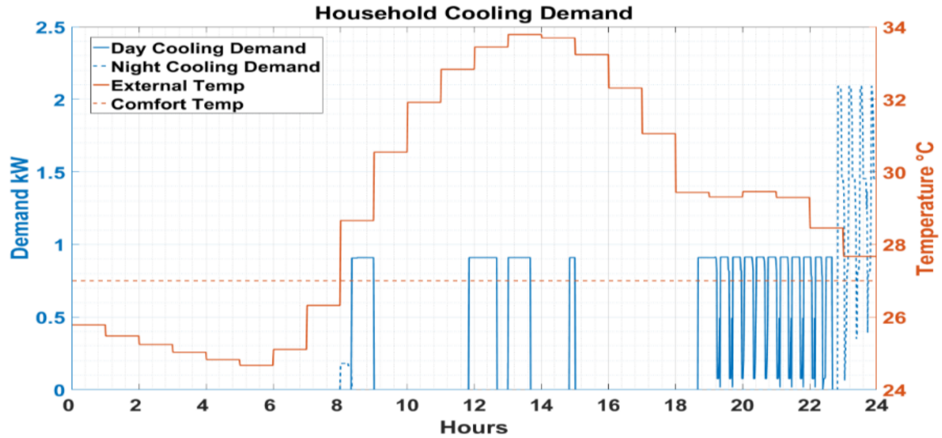


Figure 4-15 Cooling Demand from a 27°C thermal comfort threshold

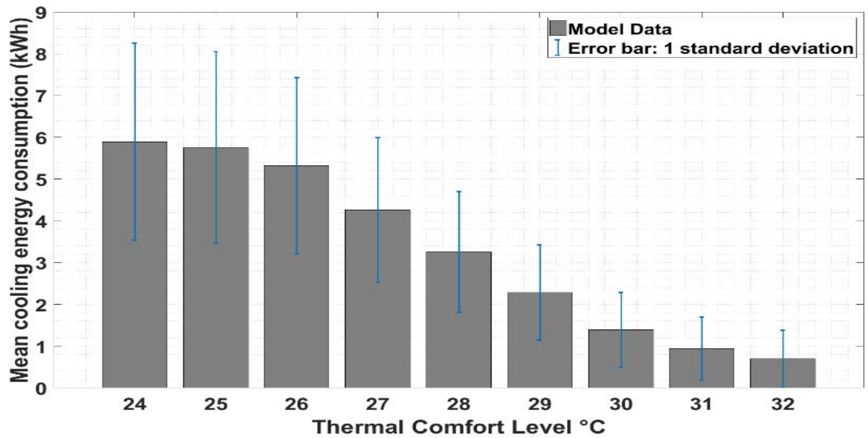


Figure 4-16: Cooling Demand by thermal comfort

4.6.2 Building Demand

Using the multi-zone cooling modelling approach which calculates the cooling energy for each building zone, the bedroom and living room cooling demand are simulated separately. The bedroom windows contribute minimal heat gains via solar radiation as the room ACs operate between night and early morning. The solar irradiance contribution from east and west facing walls, where bedroom windows are located, is higher than that of the south and north walls (Figure 5-20). At night, the room AC model does not capture the retention of heat from solar irradiance on the west facing wall by the room components prior to activation of the AC. In the morning, the impact of solar irradiance heat gain from the east facing wall is constrained due to the early household waking hours obtained from the survey. The contribution of window solar radiation to heat gains in the living room is higher than that of the bedrooms due to the active absorption of solar irradiance by the living room windows during the day as these are more south facing.

While a measure of variability in the building orientation has been included in the model, the solar irradiance impact on household cooling energy consumption between the different orientations is minimal.

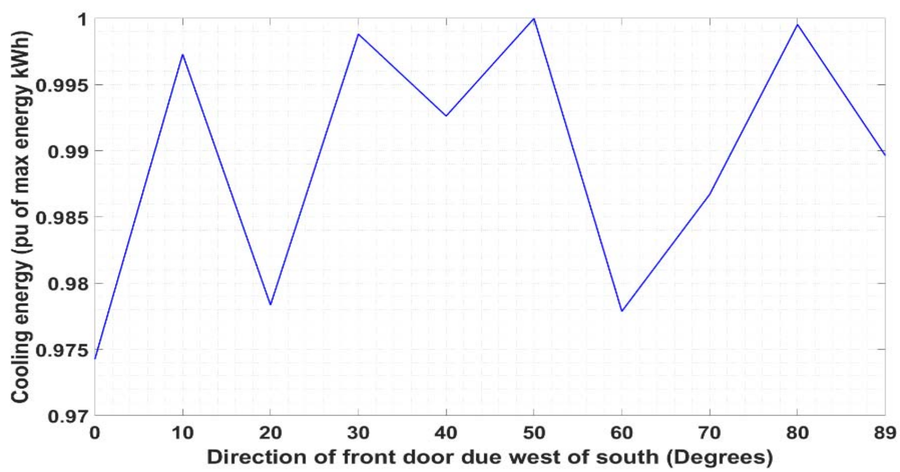


Figure 4-17: Cooling load by Building orientation

This is shown in Figure 4-17 which shows the cooling energy consumption at building orientations in steps of 10° due west of south. The difference between the cooling load at the worst case orientation (50° SW), which is the orientation of maximum cooling demand, and the best case orientation (0° SW), the orientation of minimal cooling demand is 2.6% which is acceptable, as any significant disparity might require a resizing of the cooling system of the building profiles (Office of Energy Efficiency and Renewable Energy, 2011). The peaks and drops are pronounced due to the high resolution of the cooling energy demand to show sensitivity, a smoother curve will be otherwise obtained.

The influence of the building type on energy demand is shown in Figure 4-18. There is an increase in energy consumption with an increase in the number of rooms assigned to the building. The annual aggregate mean (± std. dev.) energy use by building type shows whole buildings have the highest consumption at 4.8 (±0.7) MWh, duplexes use 4.0 (±0.6) MWh, flats use 3.6 (±0.6) MWh and single-room apartments use 3.1 (±0.5) MWh. Even though the contribution of rooms to energy consumption is limited to cooling demand, appliance ownership increases with the number of rooms in the building as larger buildings are assigned to the customer tariff classes with higher appliance ownership levels, which translates to an increase in energy consumption per building type. The model results compare well with the UK building energy survey for similar building types (Department of Energy and Climate Change, Intertek Testing and Certification Ltd., 2016).

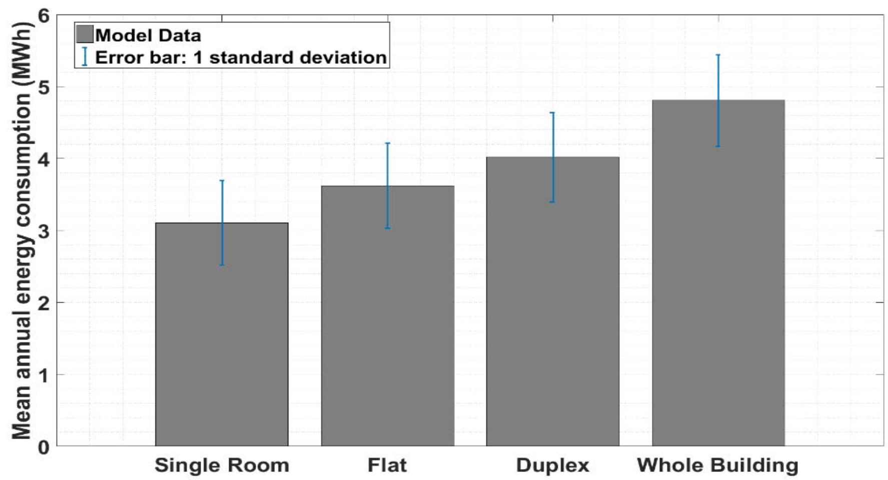


Figure 4-18: Energy consumption by building type

4.7 Validation

The UNDP residential metering campaign report is the data source used for validation in this study (United Nations Development Programme, Energy Commission of Nigeria, Federal Ministry of Environment, Global Environment Facility, 2013). Monthly household energy measurements were taken in 6 different states between March 2012 and February 2013. The measurements in Abuja FCT were taken in 2012 between March and April. With a small sample size of households (35) measured in each of the locations, the aggregate measured results for Nigeria and Abuja have been used to validate the model. 2012 MERRA-2 data has been used in the model for this validation. While full year energy estimates have been provided in the report, with a significant portion of the data obtained from bimonthly measurements, it would appear the annual estimates have been extrapolated from the bimonthly data. Information on the building types and residential tariff classes of the participating households in the study are not provided.

Despite these limitations, validation aims include assessing the model energy output in comparison to the measured and extrapolated estimates and analysing the load profiles produced from both studies.

Figure 4-19 shows the relative contribution of measured appliances to the total household demand. The error bar represents a 6% error between the total measured data and the total model energy consumption data. Air conditioning demand contribution from the model is 32% compared to 25% for the measured homes in Abuja FCT, and 17% for Nigeria. The model output represents a full year estimate while the measured data was obtained for just two months. With monthly variability in weather conditions, measurement data for two months is insufficient to predict an annual trend, however, it serves as an assessment tool to ensure the model output is within reasonable estimates. The difference between the power ratings of ACs measured and those used in the model, could also contribute to the disparity. The averaging effect on the aggregate cooling demand for Nigeria will also be impacted by the diversity in seasonal patterns across the study locations.

The energy contribution of cold appliances is similar between the model and both measured datasets. The energy from unknown appliances contributes 47% and 42%, for Nigeria and Abuja, respectively, while the energy contribution from other appliances in the model is 35%.

Overall, despite the limitations of the measurement campaign data estimates including the assumptions on household appliance power ratings, with a 6% difference in average household energy consumption between synthetic and measured data, the model is considered able to simulate residential energy usage for Nigerian households.

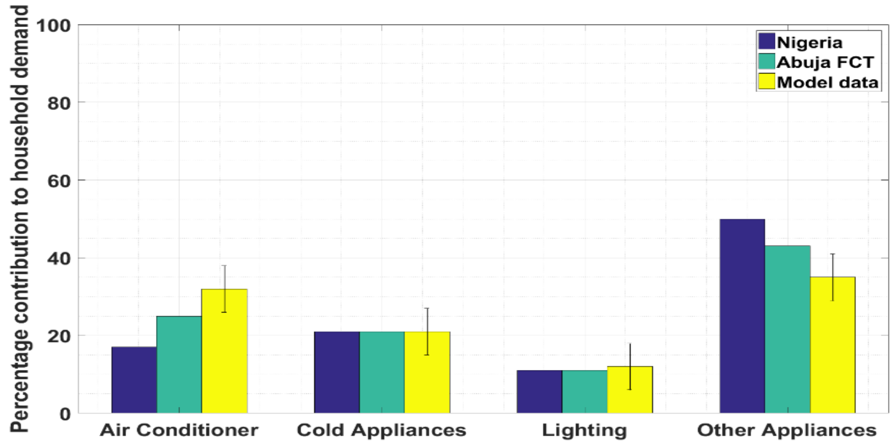


Figure 4-19: Relative demand contribution by appliance type

Daily load profiles of the model and measured data for Abuja FCT are presented in Figure 4-20. It shows the normalized aggregate mean monthly and individual month load profiles for the dry season months between February and April, during which the measurement campaign for Abuja FCT was undertaken.

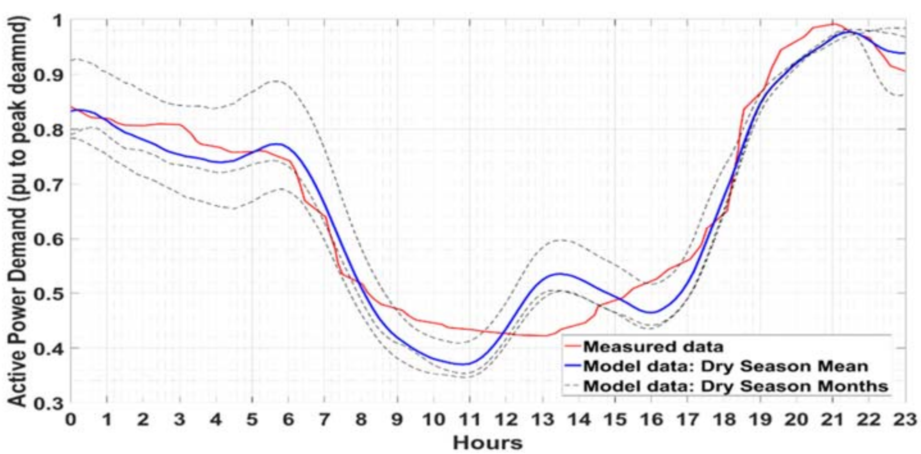


Figure 4-20: Residential load profile: Model vs Measured data

There is a good similarity between both profiles, with peaks occurring at same period in the morning and night. The model data shows an earlier pick up of afternoon (12pm) load compared to the model results, and this could be attributed to the concentration of activities based on the time resolution of the survey questionnaire. Early morning temperatures gradually increase over the dry season, with February having the coolest mornings and April, having the warmest mornings. This impacts the early morning cooling load and the household load profile for those months as shown in the plot. The correlation coefficient, which measures the quality of fit between the model load profile and the measured load profile, has a value of 0.97, while the root mean squared error (RMSE) between both load profiles is 0.04. With a mean absolute percentage error of 6% between the measured and model energy consumption data, the model is considered suitable to simulate residential load profiles for Nigerian households.

4.8 Summary

This chapter analysed and presented a modelling suite for simulating electricity demand. It investigated the requirements for modelling residential electricity demand and also presented the results of a residential electricity consumption survey undertaken as part of this research to gather input data for the model. A weather sensitive stochastic model based on socioeconomic information, survey results of household activity patterns in Nigeria and reanalysis weather data, capable of simulating residential electrical demand for Nigeria has been presented. The model has been validated against results of a small-scale residential metering campaign done in Nigeria. Peak load forecasts and demand curve patterns for Nigeria will be further developed and discussed in the next chapter

Chapter 5
Peak Demand Estimates for Nigeria

The aim of this chapter is to present and analyse reasonable estimates for the peak electricity demand for Nigeria. It is achieved by constructing a national demand curve by combining the residential peak demand forecasts from this research and non-domestic demand forecasts from another study. In order to estimate demand, a baseline study is required from which projections are made. However, the uncertainty in peak demand must be accounted for in the baseline study. This uncertainty is treated by applying a scenario approach to the socioeconomic data. The results of this chapter represent the baseline estimates for 2016.

Using the presented methodology, the residential load model presented in Chapter 4 generates the demand data required for developing annual demand patterns for each customer tariff class within a DisCo. An overview of this approach is shown in Figure 5-1. Each state under a DisCo is divided into customers by tariff class. This allows for the socioeconomic mapping of electrical appliances and building stock type by states in Nigeria onto the customer tariff classes.

Socioeconomic analysis is done using three appliance ownership scenarios for the entire country. A weather sensitive annual demand pattern is obtained as the model demand output responds to variability in ambient conditions in the various states.

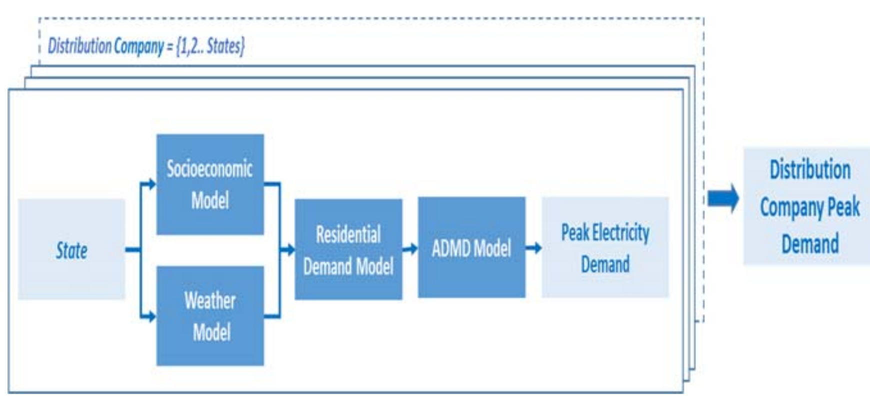


Figure 5-1: Overview of Residential Demand Modelling Approach

5.1 Socioeconomic Analysis

Socioeconomic residential customer modelling for each state is performed using national statistics available from the National Bureau of Statistics (NBS), as well as customer distribution data available from Nigeria Electricity Regulatory Commission (NERC). Published socioeconomic parameters for Nigeria are introduced into the residential electricity demand model to create household profiles at state level. For each state, and in each tariff class, household profiles are generated using the building stock and appliance ownership data. This section gives an overview of the representative socioeconomic drivers used in the model for Nigeria.

5.1.1 Domestic Appliance Ownership

The socioeconomic classification is done using the customer tariff classes for each DisCo and the appliance ownership is allocated to each category based on the national appliance ownership data from NBS (National Bureau of Statistics, 2016) and results of the household survey. The list of appliances used in the model is based on the statistical significance at the national level.

Ownership statistics on domestic appliances with high power ratings typical of high income residences are not available for Nigeria. Electric clothes dryers and ACs, appliances typical of wealthier Nigeria homes, have a reported national ownership rate of 0.1% and 2% respectively. Appliances such as dishwashers or hot tubs would have an even lower ownership rate and are not included in the model for this study. However, for DisCos that want to undertake network demand studies using this model, surveys can be prepared for the area of interest to determine its domestic appliance ownership and results can then be used to update the appliance list in the model.

Without market data on penetration of specific appliance types, assumptions have been made on the appliance ratings used in the model guided by (Community Research and Development Centre, 2009). For room ACs, the two main types used in Nigeria are the split unit and window unit types. The window unit comprises the entire air conditioning unit including the compressor and motors, while in a split unit, the AC components are split between an indoor and outdoor unit. In Nigeria, split unit types have five times the market demand of window types (The Japan Refrigeration and Air Conditioning Industry Association, 2017), but without information on the market demand by power ratings, a 1horsepower (760W) split unit type has been designed in the model using technical specifications available from LG, a dominant player in the domestic AC market in Nigeria (LG Electronics, 2017).

In order to forecast demand growth using household appliances, McNeil and Letschert (2010) used an econometric model to forecast appliance ownership using household income for six developing countries. Without state level household income data for Nigeria, a scenario-based approach is employed for this study. Three appliance ownership scenarios; high, medium and low, are evaluated for each customer tariff class and are presented in Table 5-1. The national appliance ownership data is included in Appendix A.

Table 5-1: Appliance ownership scenarios

Tariff Class	Low	Medium	High
R1	NBS – Rural	NBS - States	NBS - Urban
R2	NBS - States	NBS - Urban	Survey
R3 & R4	Survey	Survey – AC adjusted	Survey – AC adjusted

From the NBS data, appliance ownership is given for the rural, states (geopolitical zones) and urban levels in Table B.2. The rural level represents appliance ownership in the rural areas and has the lowest ownership rate per appliance. The urban level represents appliance ownership in the urban areas and has the highest ownership per appliance. The state level gives the individual state appliance ownership level and is less than the urban level and higher than the rural level. Appliance ownership from the household survey is higher than the urban level and is used to represent the highest appliance ownership level. This difference can be explained by the inclusion of unelectrified households with low appliance ownership in the NBS survey, thereby reducing the overall ownership data. The national appliance ownership levels used in the model is then categorised into the following, with NBS-Rural representing the data at the rural level, NBS-States representing data at the individual state level, NBS-Urban representing data at the urban level, Survey representing data collected from the household survey and the Survey –AC adjusted representing data collected from the household survey with adjustments made to the AC ownership.

For R1 customers, who are typically rural customers, the NBS-Rural is used for the low scenario. The medium scenario sees rural customers catching up to NBS-States and the high scenario sees R1 customers catching up to NBS - Urban. For R2 customers, the medium scenario sees the appliance ownership increasing from NBS - States levels in the low scenario to NBS - Urban. The high scenario sees the NBS - Urban increase to the Survey ownership level. For the R3 and R4 customer tariff classes, the low scenario uses the Survey data, with the Survey – AC adjusted for the medium and high scenarios.

Figure D- 1: Domestic appliance ownership in Nigeria – Refrigerator

and Figure 5-3 show maps of residential ownership of ACs and microwave ovens state level. Maps showing the ownership of selected appliances at state level are shown in Appendix D. Figure 5-4 shows the presentation of the geopolitical[6] household non-farm income distribution at state level (National Bureau of Statistics, Federal Ministry of Agriculture and Rural Development, World Bank, 2016) and Figure 5-5 shows the Cooling Degree Days in Nigeria. Where state level data is unavailable for income and certain appliances, averages for the geopolitical zones have been used.

The ownership concentration of high power rated appliances such ACs (Figure 5-2) and microwave ovens (Figure 5-3), is higher in the southern located DisCos of Benin, Eko, Enugu, Ibadan, Ikeja, and Port Harcourt compared to the other distribution companies. Ownership of such appliances is dependent on household income as shown by McNeil and Letschert (2010) and is evidenced by the household income levels in the states served by those DisCos (Figure 5-4). For ACs, ownership is lower (Figure 5-2) in the warmer states (Figure 5-5) that make up Kaduna, Kano, Yola DisCos compared to cooler states that make up Benin and Port Harcourt Discos. This further reflects the impact of income on appliance ownership, as the income levels of the states with higher AC ownership, is higher than those in the warmest states with lowest ownership rates. As the income levels rise in the warmer states that require cooling, it will lead to a rise in cooling demand in the distribution regions where they are located.

The ownership of cold appliances (Figure D- 1 and Figure D- 2) across the country also follows the income distribution. For refrigerators, ownership is lowest in the DisCo regions of Jos, Kano, and Kaduna, with the highest ownership rates further south in Benin, Eko, and Ikeja. For freezers, ownership is highest in the DisCo regions

[6] The states in Nigeria are grouped into 6 geopolitical or regional zones. They are the North East, North West, North Central, South East, South West and South South.

of Benin, Eko, Enugu, Ikeja and Port Harcourt, with the rest of the DisCo regions with less than 10% ownership rates. Despite the general low ownership trend observed from the NBS (2016) report, the United Nations Development Programme (2013) residential metering campaign report based on 210 households, shows the average number of cold appliances per household in Nigeria as 1.37. Appliance ownership is also higher in Nigeria for electrified households, as the latter report was specific to only electrified households, while the former report states electrification access rates of surveyed households as 59%. Television ownership also follows the income distribution trend, resulting in a higher concentration of ownership in Benin, Eko, Enugu, Ikeja and Port Harcourt distribution companies, compared to the others. However, the ownership of fans, radios and electric irons are more evenly distributed across the country, due to their lower relative cost (Community Research and Development Centre, 2009).

As income levels increase, electrical appliance ownership could also potentially increase. Also, as the impact of climate change on temperatures increases, the need for cooling demand could also potentially increase, resulting in higher AC ownership. Increases in electrical and cooling appliance ownership will result in an increase in electricity demand (Sailor & Pavlova, 2003). Demand studies for network reinforcement and capacity expansion planning for DisCos with the least saturation of electrical appliances will be critical as income levels in those states increase. For a power market yet to attain infrastructure and electrification maturity, distribution network planning requires electrical appliance studies to assess the impact of the changes in the nature of electrical demand based on their acquisition. For example, the dynamic demand impact of electric vehicles in developed electricity markets is still an ongoing area of research (Richardson, et al., 2012), (Soares, et al., 2013), (Karfopoulous & Hatziargyriou, 2016).

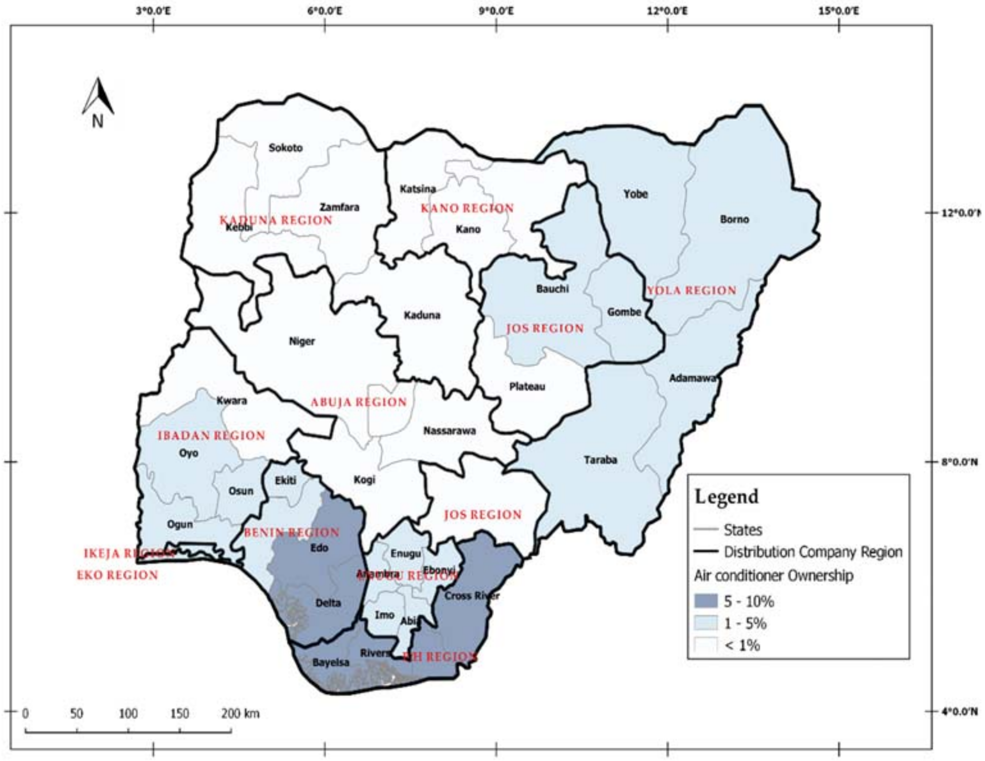


Figure 5-2: Domestic appliance ownership in Nigeria - Air Conditioner

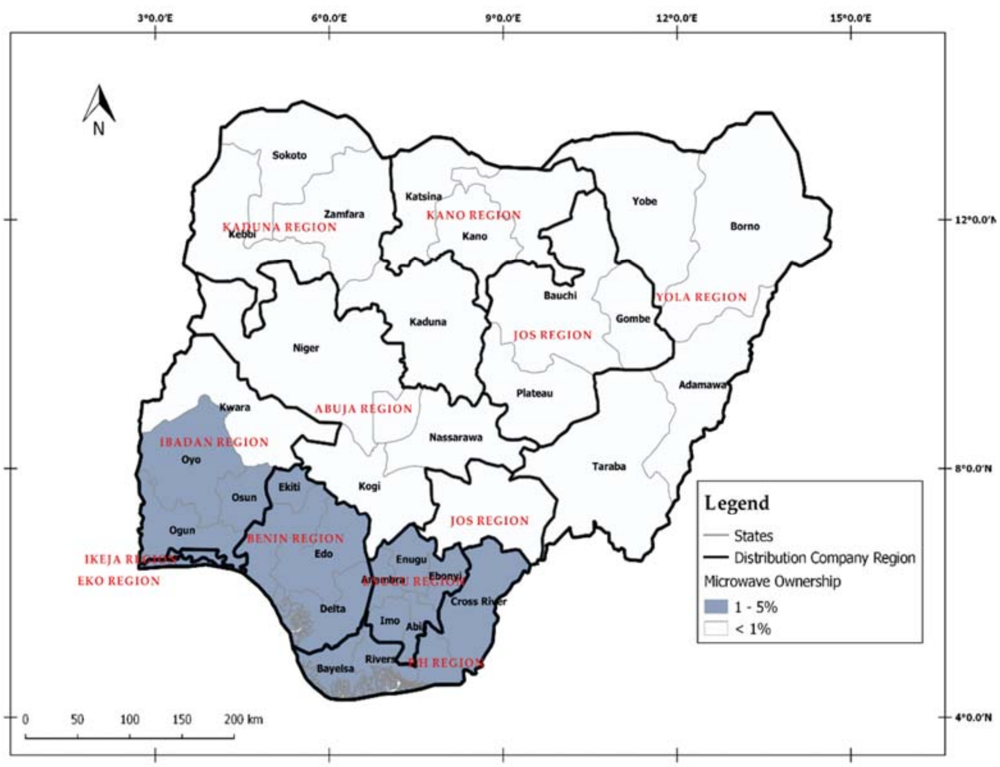


Figure 5-3: Domestic appliance ownership in Nigeria - Microwave oven

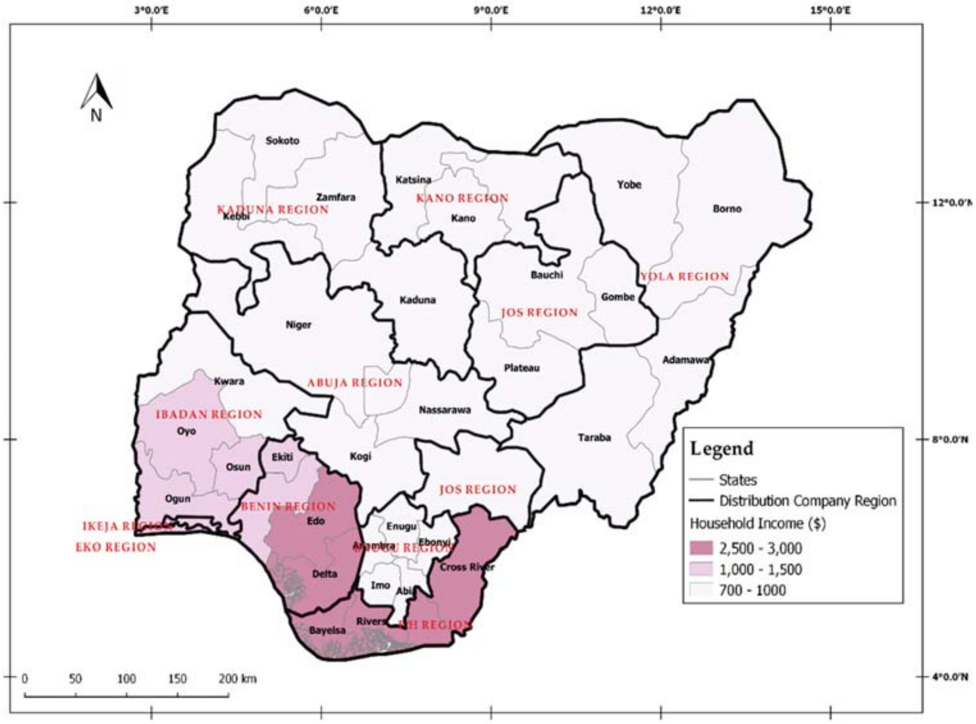


Figure 5-4: Household Income in Nigeria

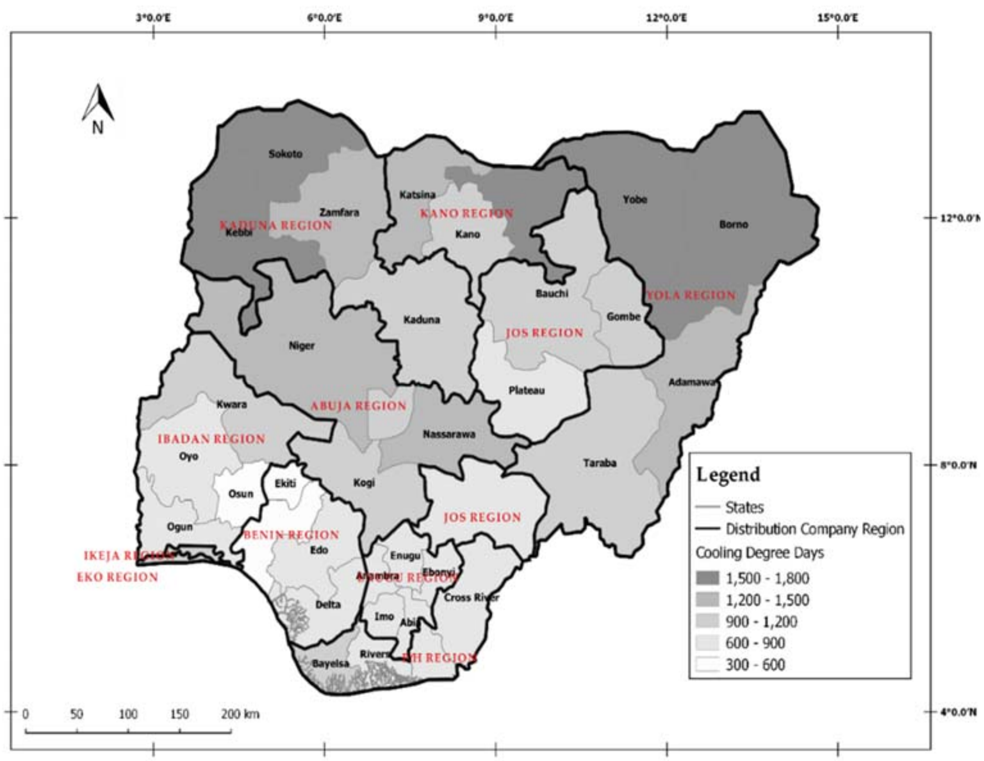


Figure 5-5: Cooling Degree Days in Nigeria (with 24°C base temperature)

5.1.2 Building Stock Type

The distribution of residential building types across Nigeria is presented in Figure 5-6 to Figure 5-9. Single room apartments shown in Figure 5-6, are inhabited by 68% of households across the country, with similar prevalence across the distribution companies. Due to the relatively smaller floor areas of single room apartments compared to the other building types, it is expected that they would consume less energy (Leahy & Lyons, 2010). The absence of additional rooms in single room apartments limits the ownership of electrical appliances, and also results in lower consumption of energy for space cooling. With plans in place by the Nigerian government to reduce its housing deficit of 17 million units (Ayedun & Oluwatobi, 2011), the building types selected to bridge this gap will have an impact on electricity demand if the average energy consumption per unit area of the selected buildings is higher than that of the single room apartments that currently dominate the housing stock in Nigeria. 25% of households live in whole buildings (Figure 5-8), the majority of which are in the Enugu, Kaduna and Port Harcourt regions. 6% live in blocks of flats (Figure 5-9), the majority of which are in the Abuja, Ibadan and Port Harcourt regions. The remaining 1% live in duplexes and other building types (Figure 5-9).

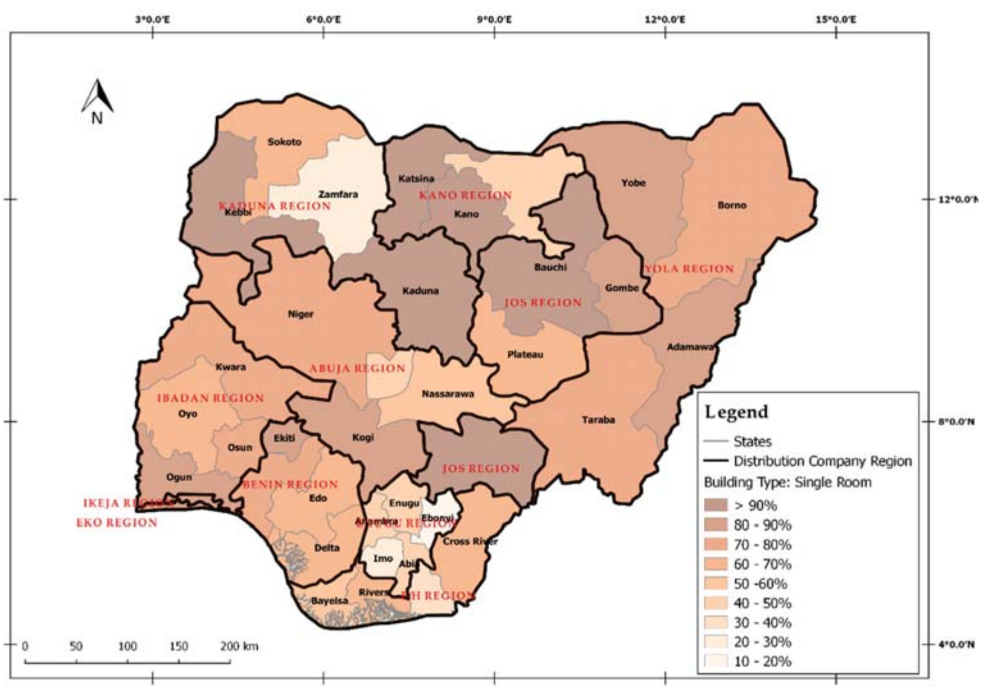


Figure 5-6: Residential Building Type – Single room

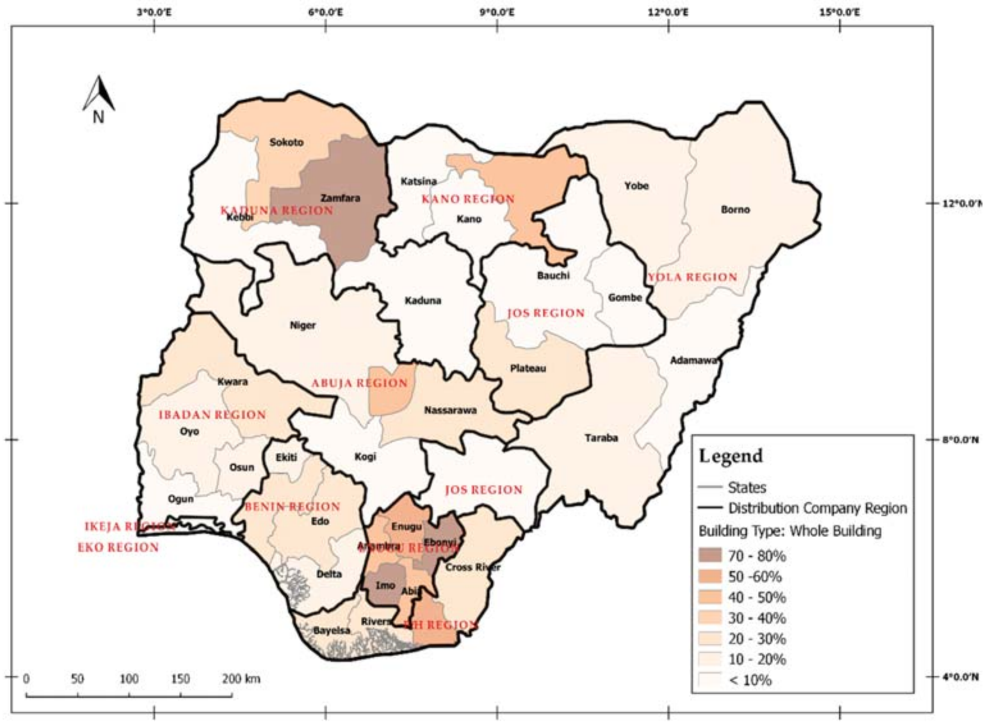


Figure 5-7: Residential Building Type – Whole Building

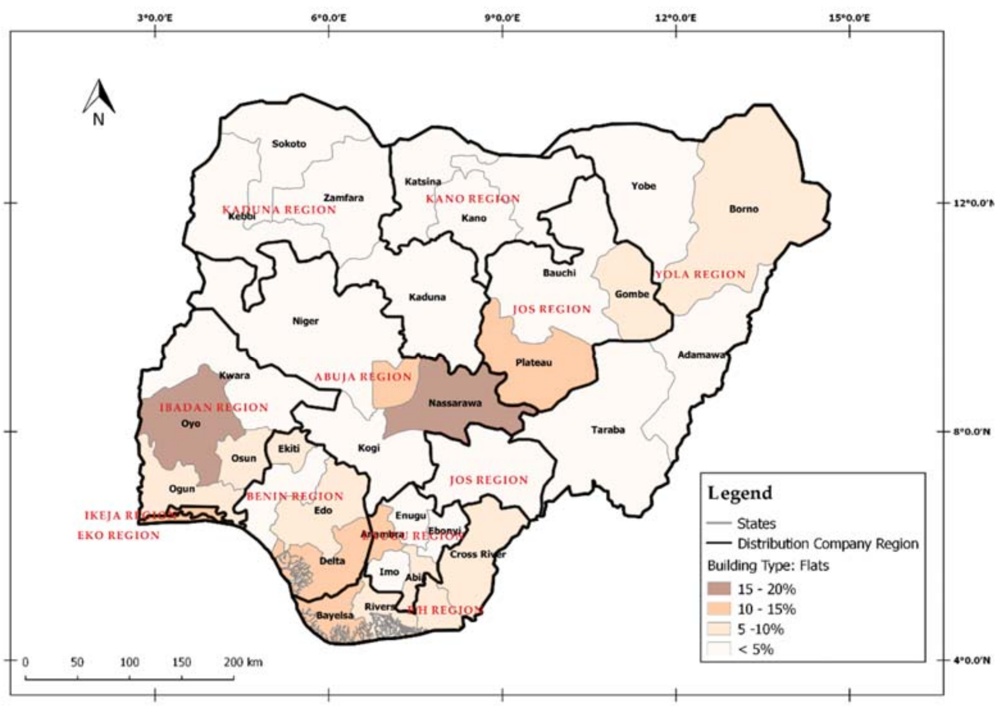


Figure 5-8: Residential Building Type – Block of flats

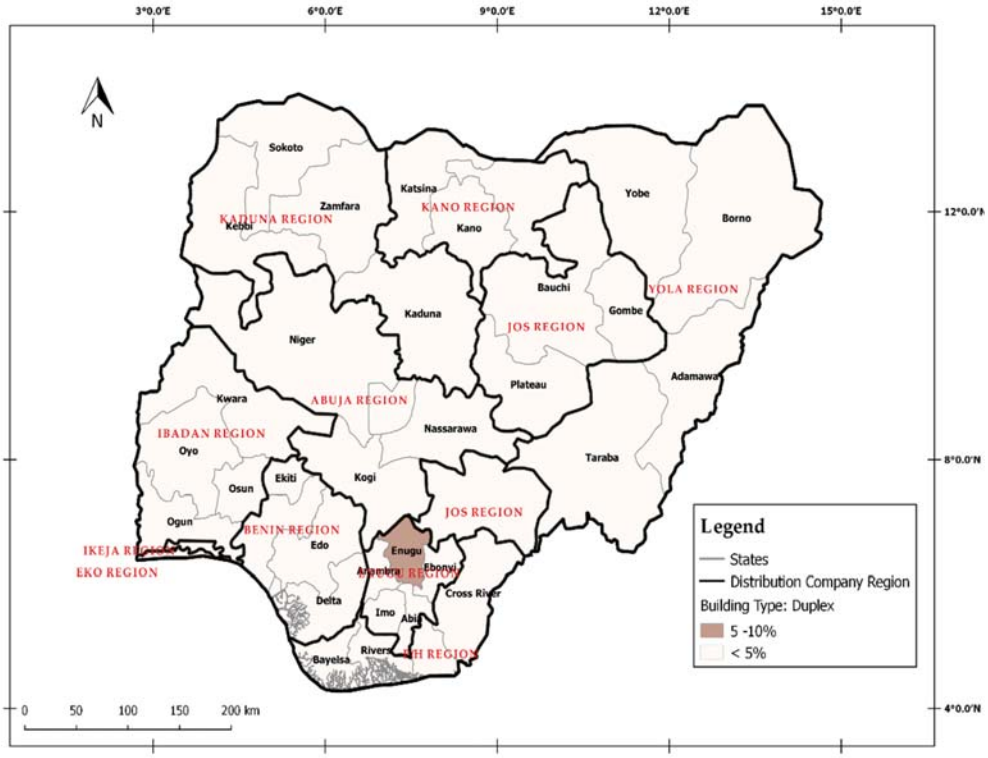


Figure 5-9 Residential Building Type – Duplex

5.1.3 Residential customer population

Domestic electricity customer population data for each DisCo has been obtained from NERC (Ohajianya, et al., 2014). The customer population by tariff class is aggregated for each DisCo in the NERC reports. These numbers have been disaggregated for each state under a DisCo region by using a 2009 unpublished demand study report for the defunct power utility company of Nigeria. These figures are presented in Table 5-2.

Table 5-2: DisCo customer population

Customer Tariff Class	2007 Population ('000)	2015 Population ('000)
R1	224	113
R2	3,104	5,334
R3		4.6
R4	328	0.3
R5		N/A
Total	3,656	5,451

The business unit customer population by tariff class for each DisCo in the 2009 report is used for the disaggregation analysis. Since 2009, residential tariff reclassifications have been undertaken which have seen the R5 tariff class subsumed by the R4 tariff class and have also affected the other customer tariff classes

Maps of Nigeria showing the distribution of residential customers by states are presented in Figure 5-10 to Figure 5-12. Figure 5-13 and Figure 5-14 show the electrification rate and population in Nigeria, respectively.

The urbanisation of Lagos has resulted in the absence of the typically rural R1 customers in Eko and Ikeja. This effect is further seen as Eko has the highest number of R3 and R4 customers (Figure 5-12). R4 customers, which make up the highest customer demand category, can be found mainly in Abuja, Benin, Eko and Port Harcourt, with marginal representation in the others except Kano and Ibadan, which have zero representation.

With a population of over a 160 million people, the electrification rate shown in Figure 5-13 shows a significant potential for residential demand growth as the national electrification rate is less than 50%, resulting in many households unconnected to grid supply. While the electrification rate corresponds to the population size (Figure 5-14) for Abuja, Benin, Eko, and Ikeja; the electrification rate is inadequate in the other distribution companies, particularly in Kano, Kaduna and Yola. For Kano, Kaduna and Yola, covering states with a low-income population and warm temperatures, improvement in income levels will translate to a significant increase in electricity demand (McNeil & Letschert, 2010).

For the R3 and R4 customers, assumptions are made to determine the average number of customers each customer tariff class represents. R3 customers are typically small estates, while R4 customers are typically large estates. Estimates are made using historical energy reports (Power Holding Company of Nigeria, 2009), the Multi-year tariff order (NERC, 2015) and recent available data for Abuja and Ikeja distribution companies. For R3 customers, an estimate of 50 households is used to represent a small estate for all states in Nigeria. For the R4 customers, an estimate of 80 households is used to represent the customers in large estates.

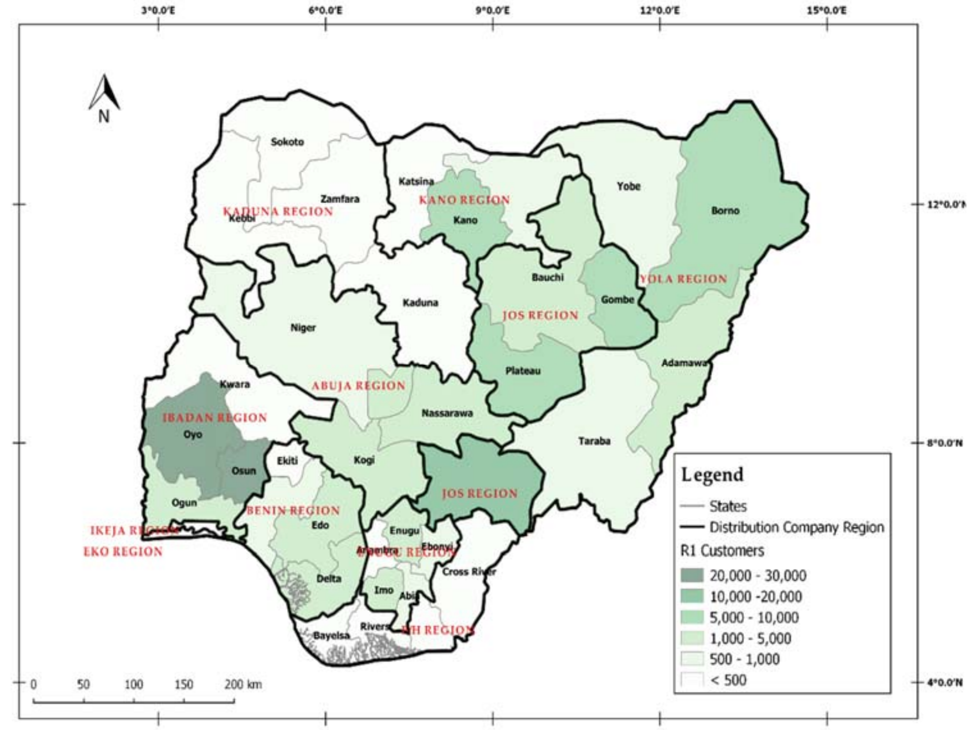


Figure 5-10 Residential Customers in Nigeria – R1 Tariff Class

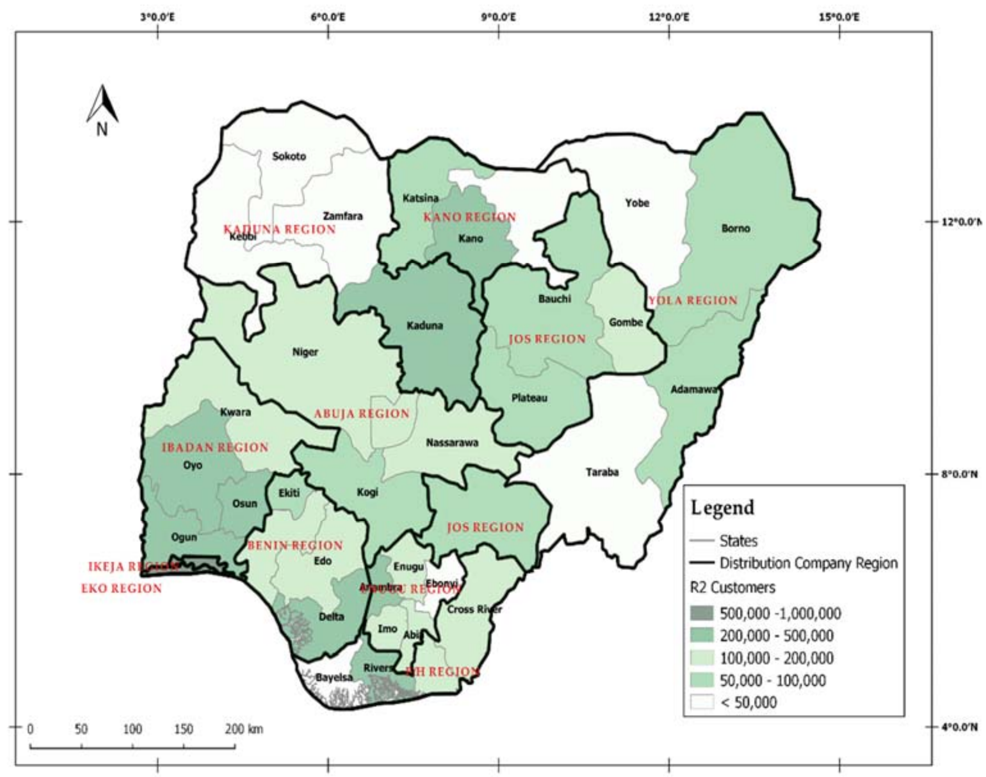


Figure 5-11 Residential Customers in Nigeria – R2 Tariff Class

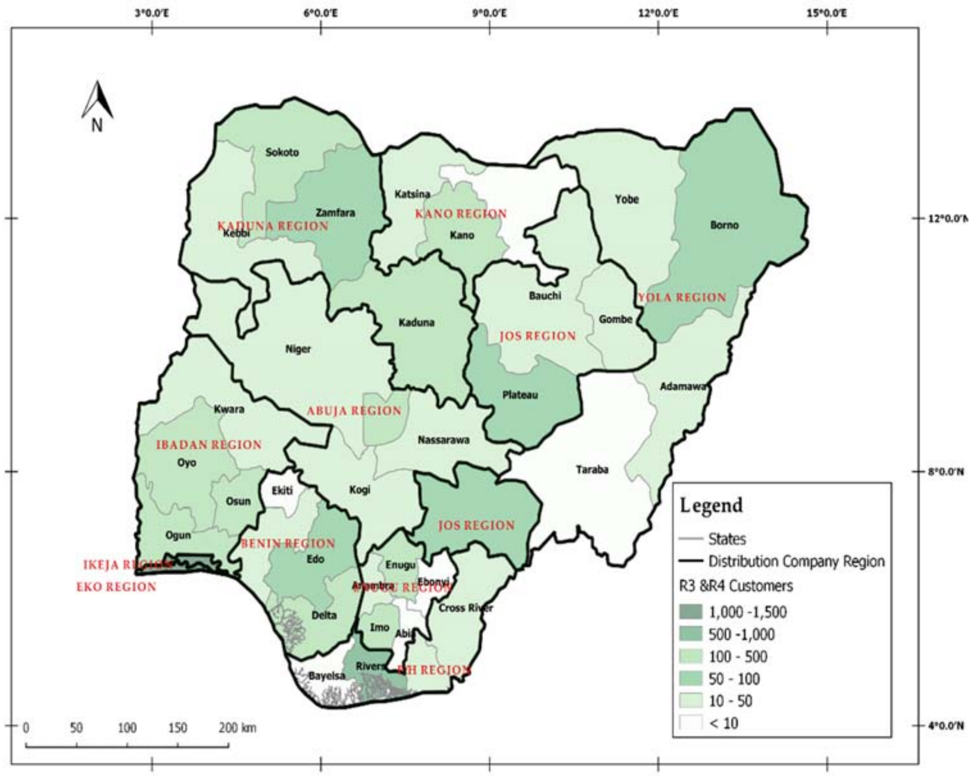


Figure 5-12 Residential Customers in Nigeria – R3 & R4 Tariff Class

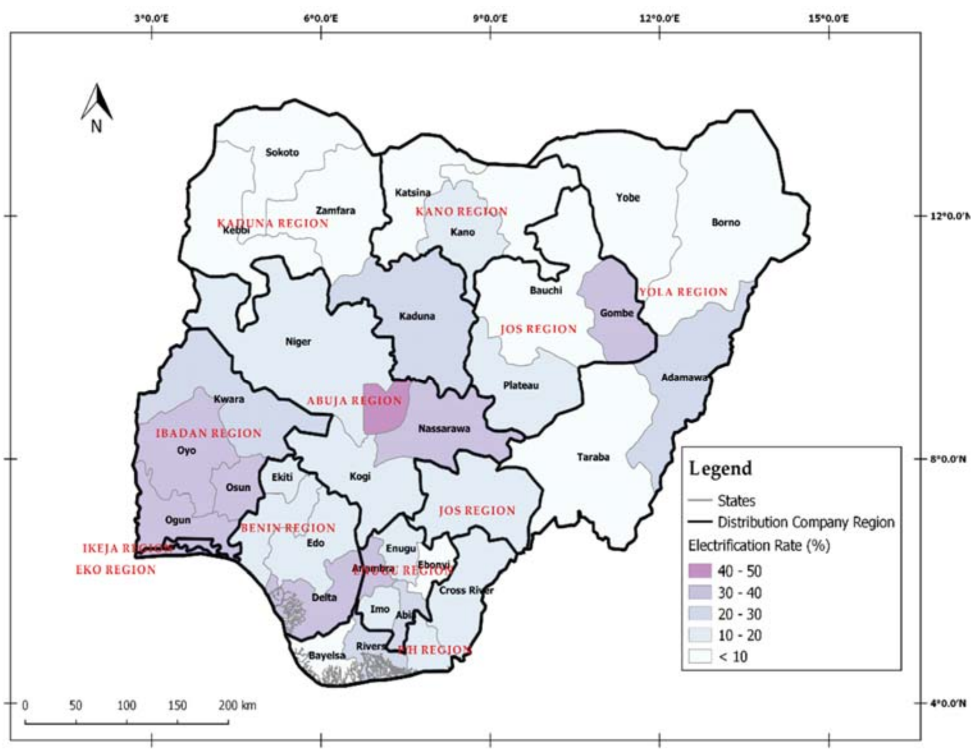


Figure 5-13 Electrification rate in Nigeria

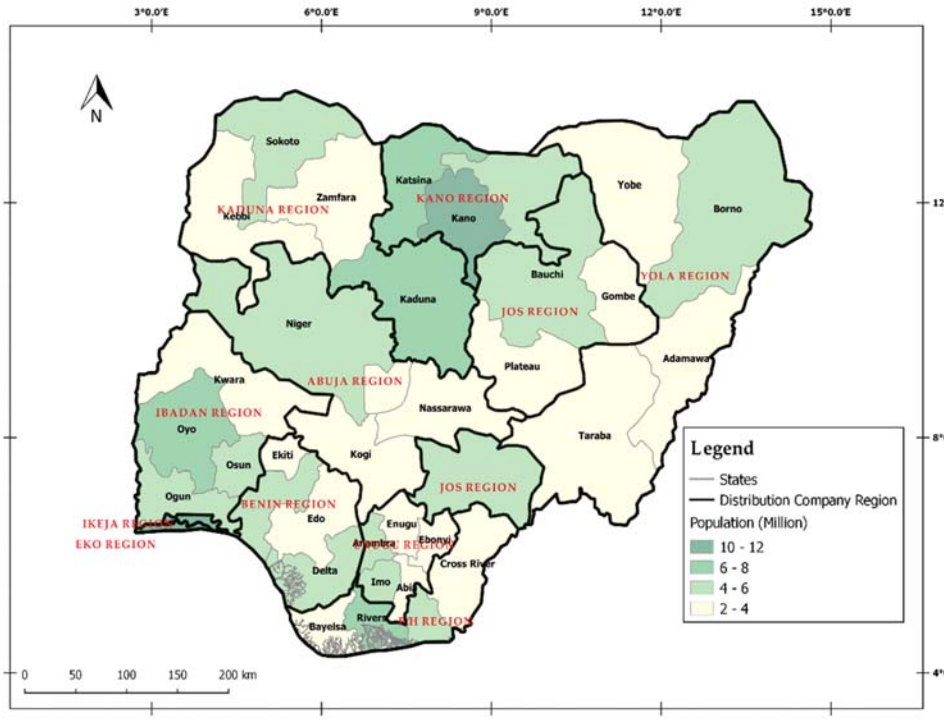


Figure 5-14 Population of Nigeria (NBS, 2012)

5.2 Weather Analysis

The weather in Nigeria is defined by two seasons, rainy and dry. A map showing the average typical rainfall days across the country is presented in Figure 5-15. The rainy season typically starts in February in the southernmost parts of the country, gradually progresses northwards in time, and finally commences in June in the northernmost regions (Nigeria Meteorological Agency (NIMET), 2016). In the south of the country, the rainy season is typically between February and October, while in the north, it occurs between June and September. The dry season commences in October in the north of the country, and typically lasts till May. In the south of the country, the dry season lasts between November and January. The dry season is characterised by dry dusty winds, hot midday temperatures and cooler temperatures at night.

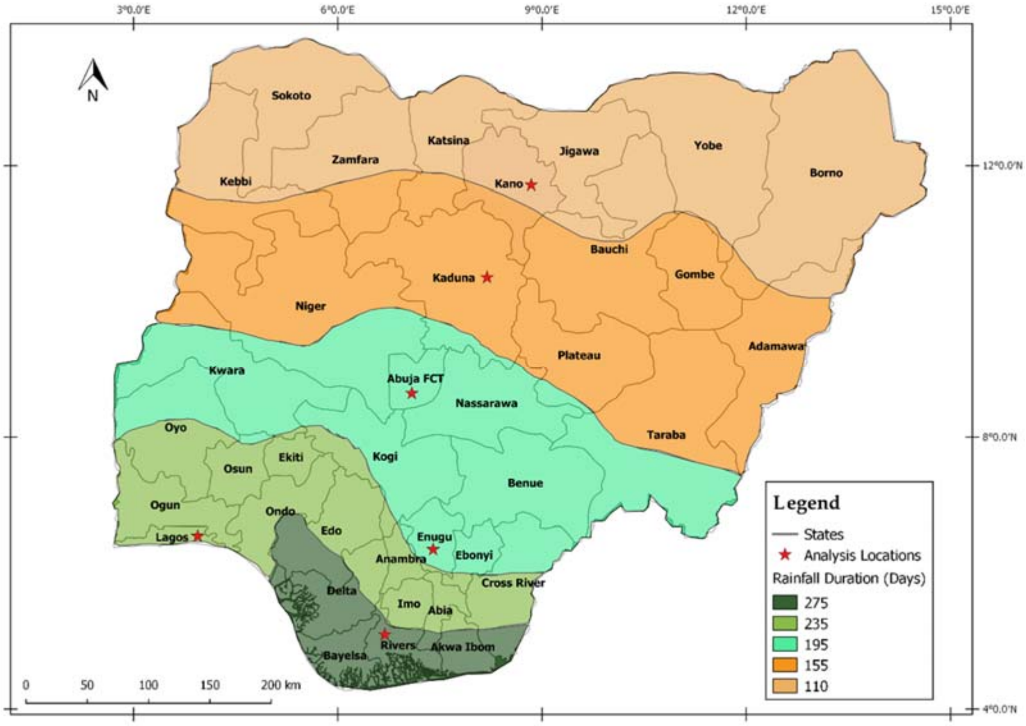


Figure 5-15: Map of Nigeria by average rainfall days

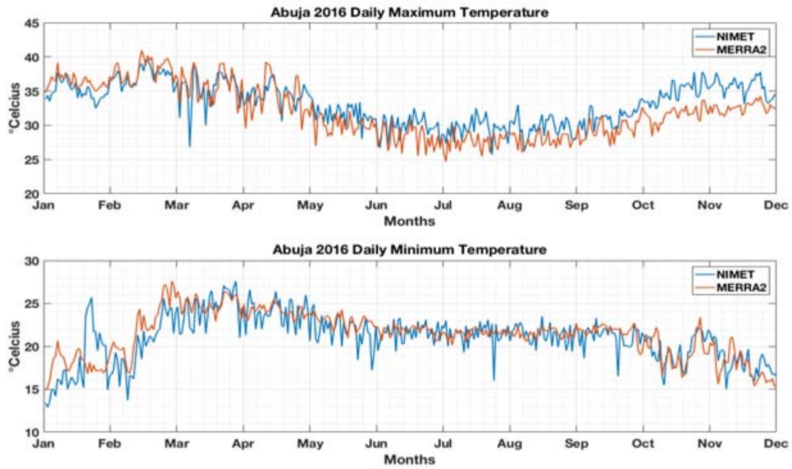
5.2.1 Temperature

The suitability of MERRA-2 temperature data for inclusion in this model is dependent on its accuracy in predicting weather patterns in Nigeria. To perform this analysis, MERRA-2 temperature data was compared to measured data from NIMET. Daily temperature data for states across the different climatic zones has been obtained from NIMET, with MERRA-2 temperature data extracted for the same locations. Temperature data from NIMET includes the maximum and minimum temperatures, with the daily averages calculated from both as a direct average. A similar methodology has been applied to the data from MERRA-2 to obtain the daily averages. The root mean squared error (RMSE), mean bias error (MBE), and maximum percentage error (MPE) tests have been performed on both data sets to assess the predictive accuracy of MERRA-2 for Nigeria's temperature. The annual onset and cessation dates for the rainy season in Nigeria have been obtained from NIMET for this analysis. Results of the analysis for full year, dry and rainy seasons are summarized in Table 5-3. Figure 5-16 and Figure 5-17 show the full year temperature comparisons of the states used for the analysis.

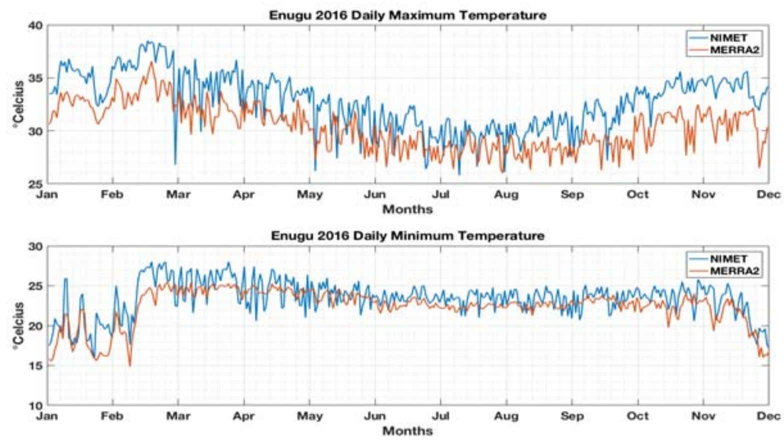
Table 5-3: Temperature predictor errors

		(°C)		(%)
Location	Rainy Season (Days)	RMSE	MBE	MPE
Abuja FCT				
Full Year		1.54	1.30	
Dry Season		1.87	0.67	20.61
Rainy Season	Apr 20 – Nov 11 (205)	1.37	0.64	12.92
Enugu				
Full Year		2.08	1.86	
Dry Season		2.50	2.30	17.57
Rainy Season	Mar 24 – Dec 5 (256)	1.87	1.67	16.23
Kaduna				
Full Year		2.23	1.82	
Dry Season		2.38	0.89	19.54
Rainy Season	May 5 – Nov 9 (188)	2.08	0.94	17.79
Kano				
Full Year		1.83	1.46	
Dry Season		2.09	0.98	26.32
Rainy Season	May 23 – Oct 27 (157)	1.58	0.51	17.68
Lagos				
Full Year		1.39	1.14	
Dry Season		2.18	1.94	15.38
Rainy Season	Mar 18 – Dec 10 (267)	1.29	1.08	11.67
Rivers				
Full Year		1.30	1.00	
Dry Season		1.56	1.30	13.04
Rainy Season	Mar 1 – Dec 23 (297)	1.17	0.97	16.17

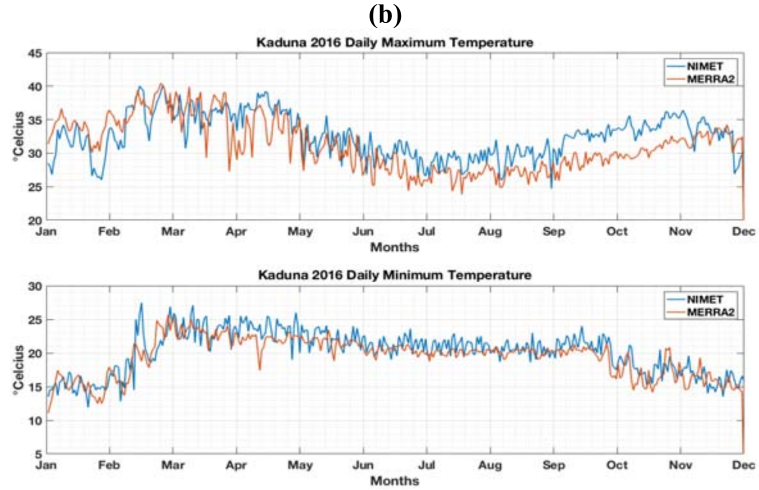
The prediction bias, given by the MBE, has an error range of 0.64°C and 1.86°C for the full year, 0.51°C and 1.67°C for the rainy season, and 0.67°C and 2.30°C for the dry season. The MPE has a range of between 11.67% and 17.79% for the rainy season, and between 13.04% and 26.32% for the dry season. The RMSE values correspond to the magnitude of the bias obtained for each location and range from 1.30°C and 2.23°C for the full year analysis. With the exception of Kano, these errors are largely driven by the underestimation of daily maximum temperatures during the year, and are prominent during the dry season, with significant bias occurring in the southern states of Enugu (Figure 5-16b), and coastal states of Lagos (Figure 5-17b), Rivers (Figure 5-17c). For Kano, an overestimation of full year temperatures is observed. This effect occurs during the dry season, between October and December for the daily minimum temperatures, and the full year for the maximum temperatures (Figure 5-17a). While a full year marginal overestimation of daily minimum temperatures is observed in the coastal state of Lagos (Figure 5-17b), a full year underestimation of daily maximum temperatures is also observed.



(a)

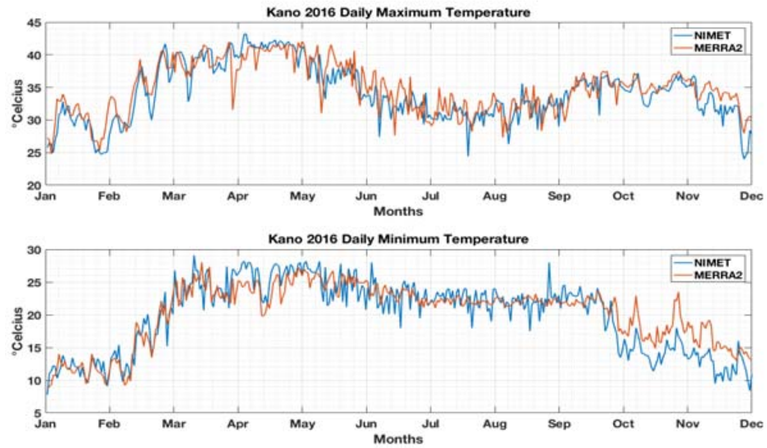


(b)

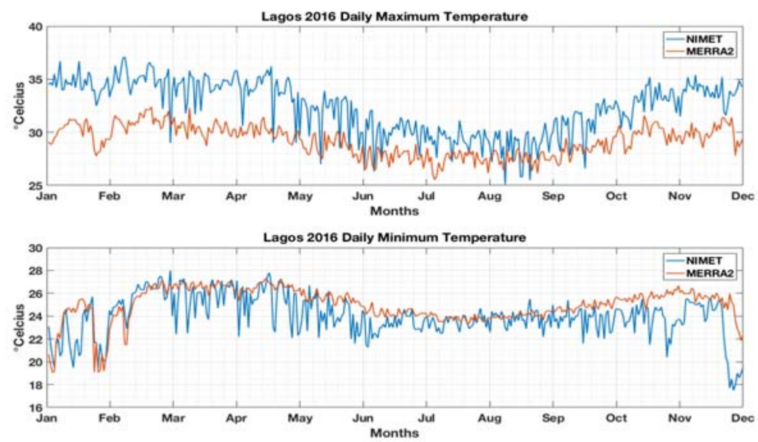


(c)

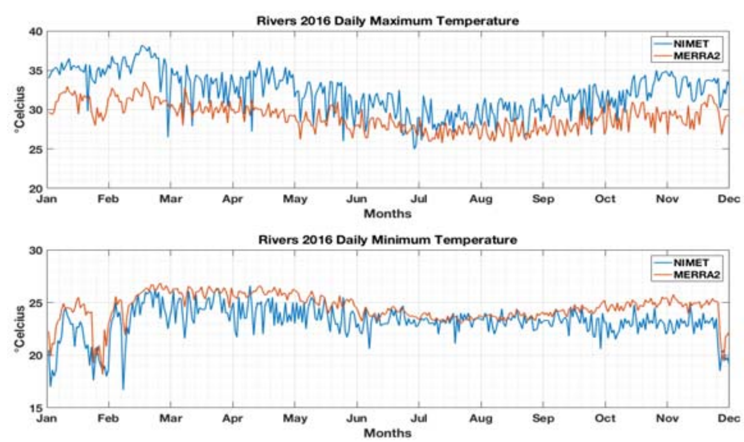
Figure 5-16: Daily minimum and maximum temperatures (a) Abuja (b) Enugu (c) Kaduna



(a)



(b)



(c)

Figure 5-17: Daily minimum and maximum temperatures (a) Kano (b) Lagos (c) Rivers

One of the possible reasons for this could be the daily clear/cloudy sky condition used in the MERRA-2 analysis, which may have dampened the predicted incident irradiance and its attendant temperature effect for the southern and coastal states. MERRA-2 spatial resolution is 50km average, which will mask local variables. Coastal effects will also be lessened. Overall, the temperature plots show a good profile and seasonal trend similarity between both temperature data sets. However, the relative seasonal bias of MERRA-2 temperature predictions for Nigeria is stronger in the dry season compared to the rainy season.

Peak cooling demand estimation for any location is based on peak temperatures of the warmest months of the year for that location (ASHRAE, 2013). Historical weather data reveals the warmest days in Nigeria occur between January and April (Nigeria Meteorological Agency (NIMET), 2016), and thus the period for which peak cooling demand estimations are required. While bias has been observed in the reanalysis data, without hourly temperature data available from NIMET, the MERRA-2 data will be used to perform this research. Bias correction which can be applied to treat the reanalysis data will require measured data from more locations across Nigeria to assess the impact on cooling demand.

5.2.2 Irradiance

NIMET records the daily irradiance at selected locations across Nigeria; however hourly irradiance data required for this analysis is unavailable. In the absence of measured data, the methods of obtaining hourly irradiance data include climatic re-analysis data (Boilley & Wald, 2015), satellite observations (Pinker & Laszlo, 1992), and calculations based on observed climatic conditions (ASHRAE, 2013). Due to data availability challenges, options are currently limited to re-analysis and calculated data. Both are compared against measured data from Nigeria. ASHRAE is used to refer to the calculated data unless stated otherwise.

Using the climatic design methodology recommended by ASHRAE, and climatic design conditions made available from ASHRAE (2013), the global irradiance for the measured location is estimated. The ASHRAE database does not include data for Nigeria, therefore the design conditions of the weather station (co-ordinates 6.35°N and 2.38°E) in the Republic of Benin, has been used for Lagos (co-ordinates 6.60°N and 3.35°E). Both points lie in the same climatic zone.

Irradiance measurements taken by the National Centre for Energy Efficiency and Conservation using a "CMP11" pyranometer has been used in this study. MERRA-2 irradiance data has been used as well. The measurements were taken at a 1-minute resolution over a 19-day period between December 2014 and January 2015. The MBE and RMSE results are presented in Table 5-4. Figure 5-18 and Figure 5-19 show the GHI and mean hourly GHI comparisons.

Table 5-4 Irradiance predictor errors

Data source	MERRA-2			ASHRAE		
	(W/m^2)		(%)	(W/m^2)		(%)
	MBE	RMSE	MPE	MBE	RMSE	MPE
Entire Period	15.1	89.5		41.0	96.6	
Time of Day Bias						
Low (7am-9am), (3pm-7pm)	92.1	75.4	129.8	165.2	86.3	235.4
Moderate (9am -11am), (1pm-3pm)	52.8	157.2	98.2	215.5	161.9	134
Peak (11am – 1pm)	36.4	163.4	80.1	112.4	183.4	88

It can be observed that the magnitude of errors in the analysis occurs within the moderate to peak periods of the measured data as both methods overestimate the peak irradiance for most days, with larger bias observed from the ASHRAE data for the MBE, MPE and RMSE. While impacted by the cross-border weather climatic detail input, the magnitude of errors observed in the ASHRAE data necessitates the use of the re-analysis data for the model. The interpolation of monthly clear sky conditions between the 21st days of successive months might also contribute to the error magnitude observed. In any case, the cross border climatic design conditions approach cannot be used extensively to model irradiance across Nigeria.

The 19-day period of measurement, which occurred during the dry season, is too short to allow for a seasonal study (Figure 5-18). GHI measurement results for the rainy season in this location, which lasts for about 267 days, will be required to draw conclusions about the overall goodness of fit. As seen with the temperature analysis, MERRA-2 prediction for Nigeria's coastal areas during the rainy season is better compared to the dry season. While the study of the source and bias of errors between measured and MERRA-2 data is beyond the scope of this study, the above analysis is necessary to define the limitations of the input of data for this location (Boilley &

Wald, 2015). Measurement results for other locations mapping to the MERRA-2 temperature predictions are unavailable.

Figure 5-20 displays the sol-air temperature plots using irradiance data from MERRA-2 and ASHRAE calculations. The plot represents the temperature conditions for Lagos on 20 January 2014. Surface orientation assignment is done using the ASHRAE convention with the south wall facing 20° due west of south. The other wall angles are relative to that. There is an overestimation of temperatures at the receiving surfaces using the ASHRAE data compared to MERRA-2 data. The difference between the ASHRAE and MERRA-2 peak temperatures at the south, east and west walls are 4.5°C, 4.7°C and 4.0°C respectively. However, at the north wall, the peak temperature observed for MERRA-2 is slightly higher than ASHRAE by 0.7°C. Considering the overall bias effect, the MERRA-2 data is preferable to ASHRAE data.

With insufficient state-wide measured data for both weather variables used in this study, bias correction cannot currently be performed. Future work will attempt to collate measured data from states in Nigeria for a weather bias correction study.

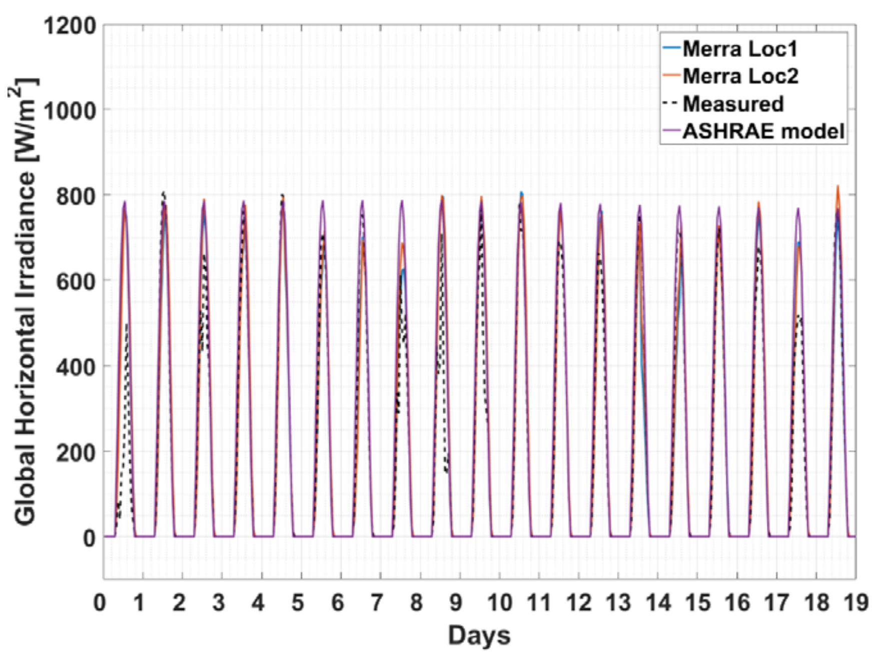


Figure 5-18 Global Horizontal Irradiance

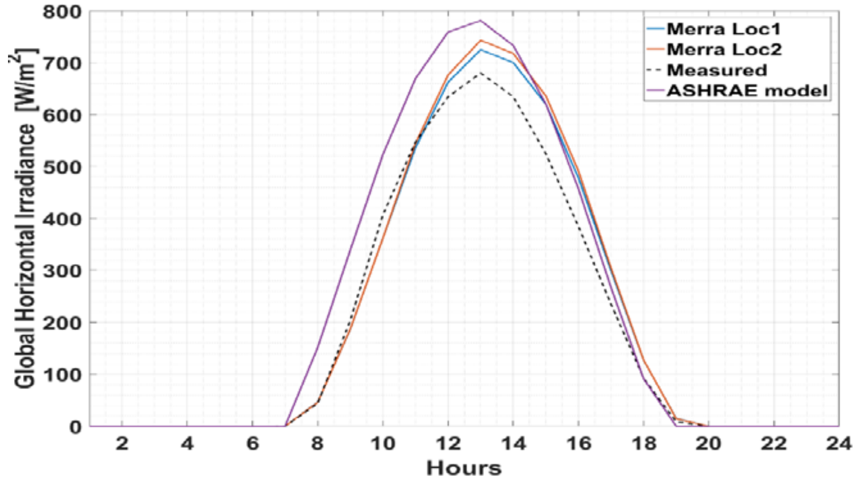


Figure 5-19 Mean hourly Global Horizontal Irradiance

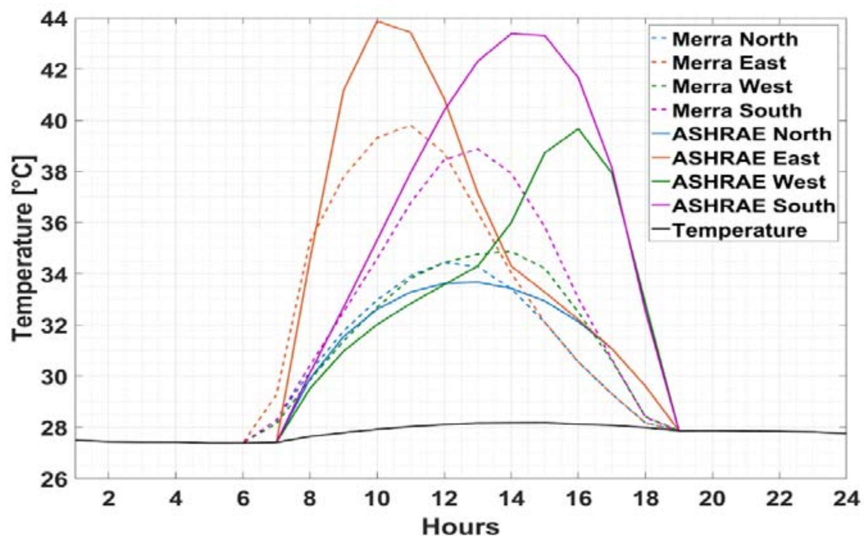


Figure 5-20 Sol-air temperature plots (MERRA2 vs ASHRAE model)

5.3 Estimating Peak Demand

The national peak demand analysis is performed on a state-by-state level to capture the demand diversity within and between the states in order to account for the differences in socioeconomic and ambient weather conditions between the states. Without significant changes in the residential demand model output using simulation sets larger than a thousand profiles, its application in simulating the entire customer population of a state within a DisCo is limited. To overcome this limitation, the after diversity maximum demand (ADMD) methodology is used to estimate the peak demand for a state by using the residential model demand output.

While the ADMD is typically applied at the end points of low voltage networks to forecast demand, estimating the ADMD in practice is a challenging exercise due to the differences in customer consumption classes at the same transformer point, except for homogenous neighbourhoods. In practice, the ADMD value is lowered due to the average demand of a diverse customer group at an estimation point. The use of the residential model enables the study of the ADMD within the same customer consumption category and limits the averaging effect on peak demand. Each state is modelled as 4 transformer points representing each customer tariff class. Customers across tariff classes can also be mixed, clustered, and served by a transformer. Customers in the same income group typically exhibit similar electricity consumption patterns.

The ADMD methodology is applied to the model output to estimate the ADMD value from the generated demand data for a set of a thousand customer profiles. The simulation is run for each day in each state, and the obtained ADMD values are then used to estimate the peak demand for each customer tariff category using the customer population. This analysis is performed for the three national household appliance ownership scenarios discussed in section 5.1.1. The peak demand can be expressed below for each of the three scenarios *S* as

$$PD_s(t) = \sum_{g=1}^{G}\sum_{n=1}^{N} RC_{g,n}\, ADMD_{s,g,n}(t) \qquad \forall s \in S \tag{5.1}$$

where *PD* is the peak demand (MW) for the DisCo in scenario *s*, *g* is each state in the DisCo region, *G* is the total number of states in each DisCo, *ADMD* is the after diversity maximum demand value (W) for each customer tariff class *n, N* is the total number of customer tariff classes, *RC* is the number of customers in each tariff class *n* and *t* is the time in minutes.

Due to the simulation time requirements of generating annual daily demand data for 1000 profiles for each of the 38 states in the 3 scenarios, the appliance demand model was split into its components, the appliance and cooling models, to generate two different demand data sets. The appliance demand model, which is independent of seasonal weather changes, was used to generate demand data for two weeks in each location. Given that the results from the survey represent typical weekly activities for each respondent, this simulation duration is deemed sufficient to estimate typical residential non-cooling appliance demand data. On the other hand, the cooling demand data which is dependent on seasonal weather changes, has been run for each day of the year in each location. The non-appliance weekly demand data is assumed to be constant for the full year and added to the cooling demand data, to obtain the full year demand data. While the computation analysis has been split between the two models, the same profile data is used for both to ensure consistency in appliance saturation.

5.4 Residential Peak Demand Estimates

The results for the non-simultaneous peak demand for the DisCos and simultaneous peak demand at the national level are presented in this section. The state level peak demand and ADMD results have been included in Appendix B. The summary results for DisCos are presented here.

5.4.1 Tariff Class Peak Demand

With the socioeconomic mapping executed at the customer tariff class level, the peak demand estimates at tariff class level are presented in this section.

R1 Tariff Class

The peak demand summary of the R1 tariff class is presented in Table 5-5. This tariff class represents the electrical demand of rural customers in Nigeria. The scenario analysis sees the transition of appliance ownership of rural customers from the NBS rural appliance ownership data in the low scenario, to the NBS state appliance ownership level in the medium scenario and finally, to the NBS urban appliance ownership level in the high scenario. The assumption here is that the rural customers become urban as the socio-economic situation in the country improves.

For the low scenario, the state ADMD values fall within the range of 214 to 247 W. This demand range falls under the very low consumption class, with a typical annual energy consumption of less than 1.2MWh/year. In the medium scenario, this increases to 248 to 1035 W, with 16 of the 38 states in the very low consumption class, and the rest in the low consumption class. Typical annual energy consumption in the low consumption class ranges between 1.2 to 3 MWh/year. In the high scenario, the ADMD values are within the range of 579 to 1129 W, which means all the states fall under the low consumption class.

The increase in appliance ownership across the states sees a 107% increase in peak demand from the low to medium scenarios, and a 41% increase from the medium to high scenario. The low to high scenarios sees a 192% increase in peak demand. The magnitude of difference across the scenarios shows the implication of socioeconomic conditions on electricity demand.

Table 5-5: Summary of R1 Peak Demand Scenario Forecasts

	Peak Demand (MW)		
DisCo	Low	Medium	High
Abuja	1.5	2.7	4.8
Benin	0.8	2.9	3.3
Eko	0.0	0.0	0.0
Enugu	0.9	2.0	2.5
Ibadan	11.4	28.8	34.7
Ikeja	0.0	0.0	0.0
Jos	6.2	7.5	17.0
Kaduna	0.2	0.2	0.4
Kano	1.8	3.0	5.1
Port Harcourt	0.2	0.5	0.5
Yola	2.1	2.9	6.1
Total	25.1	50.5	74.4

From the low to medium scenarios, the change in peak demand is highest in Benin, Enugu, Ibadan and Kaduna distribution companies, which shows the current socioeconomic and appliance ownership disparity between rural and state customers currently in that region. From the medium to high scenarios, which sees the transition from state appliance ownership levels to urban appliance ownership levels, the peak demand increase is highest in Yola, Jos and Kano, signifying the disparity in appliance ownership between customers in those states and the national urban level.

For the R1 tariff class, peak demand is largely driven by customer population. Ibadan and Jos, with the largest customer population in this tariff class, have the highest peak demand. The largely urban status of Lagos state means there are no R1 customers for Eko and Ikeja DisCos which service it. From NERC (2015), the average annual growth rate of R1 customers is projected at 6.5%, however this only contributes to 2% of the total residential customer population therefore the peak demand for this tariff class is not expected to be a significant contributor to the overall residential peak demand without significant changes in socioeconomic conditions.

R2 Tariff Class

Peak demand for all scenarios is largely driven by the R2 customer tariff class that contributes over 90% of the electricity demand in Nigeria (NERC, 2015). As this tariff class makes up 98% of total residential customers, the penetration of electrical appliances by quality (power rating and efficiency) and quantity among this customer group is significant in estimating the overall residential peak demand. Table 5-6 shows the scenario estimates for the R2 tariff class. To estimate peak demand, NBS - States and NBS – Urban appliance ownership data were used for the low and medium scenarios, respectively, while this research's household survey was used for the high scenario.

Table 5-6: Summary of R2 Peak Demand Scenario Forecasts

	Peak Demand (MW)		
DisCo	Low	Medium	High
Abuja	176	332	507
Benin	458	572	720
Eko	340	332	422
Enugu	433	469	717
Ibadan	528	629	1,047
Ikeja	518	559	685
Jos	63	242	391
Kaduna	136	195	325
Kano	103	193	300
P/Harcourt	374	401	587
Yola	64	88	148
Total	3,194	4,012	5,850

For the low scenario, the state ADMD values fall within the range of 265 to 1066 W. This demand range falls between the very low and low consumption classes. 22 of the 38 states fall under the low consumption class, with the rest falling under the very low consumption class. In the medium scenario, this increases from 591 to 1201 W, with all of the states in the low consumption class, and also sees a narrowing of the ADMD band as the national appliance ownership disparity decreases. In the high scenario, the ADMD values are within the range of 972 to 1521 W, with 4 states in the medium consumption class and the rest in the low consumption class. Typical annual energy consumption for customers in the medium consumption class is between 3 to 7.5 MWh/year.

The increase in appliance ownership across the states sees a 23% increase in peak demand from the low to medium scenarios, and a 43% increase from the medium to high scenario. Transition from the low to high scenarios sees a 76% increase in peak demand. The increase in demand is largely driven by the states that currently have relatively low appliance ownership in the low scenario, with transitions to the medium and high scenarios seeing significant increases in demand. Low appliance ownership in the states that comprise Jos, Kaduna, Kano and Yola distribution companies, result in an increase of over 100% peak demand from the low to medium scenarios.

The assumption here is that all states have caught up to the national urban appliance ownership level. Eko, Ikeja and Port Harcourt experience a marginal increase in peak demand between the low and medium scenarios, as the states involved here have relatively higher appliance ownership levels compared to the rest of the country. The high scenario, which uses the AC ownership data from the survey, provides an indication on the impact of cooling demand across the distribution companies. The impact of warmer temperatures and increased AC ownership in states across the country on peak demand is amplified in this scenario.

This impact is significantly highlighted in the states that comprise Jos, Kaduna, Kano and Yola distribution companies, resulting in an average peak demand increase of 214%. As socioeconomic conditions improve for customers in this tariff class, the DisCos servicing states currently with low appliance ownership levels are expected to experience a higher increase in peak demand compared to those servicing states with relatively higher appliance ownership levels. From NERC (2015), the average annual growth rate of R2 customers is projected at 6.3% and contributes to 98% of the total residential customer population; therefore, the peak demand for this tariff class will remain a significant contributor to the overall residential peak demand.

R3 and R4 Tariff Class

This tariff class represents customers in small and large estates. The scenario analysis uses the household survey data for all states in the low scenario and higher AC ownership rates for the medium and high scenarios. Customers in this tariff class are typically high-income customers, with high ownership rates of typical household electrical appliances. Table 5-7 shows the scenario peak demand for the R3 and R4 tariff classes.

For the low scenario, the state ADMD values fall within the range of 1054 to 1520 W, with 7 states in the medium consumption class and the rest in the low consumption class. The change in AC ownership between the medium and high scenarios does not translate to a significant change in ADMD levels, as the band for both scenarios is between 2003 to 2336 W and 2044 to 2365 W for the medium and high scenarios respectively. Increased AC ownership above 60% translates to a marginal increase in ADMD values at state level.

The increase in appliance ownership across the states sees a 67% increase in peak demand from the low to medium scenarios, and a 1% increase from the medium to high scenarios. The low to high scenario transition sees a 74% increase in peak demand. Appliance ownership saturation in the medium scenario results in a marginal increase in peak demand in the high scenario.

Table 5-7: R3 and R4 Peak Demand Scenario Forecasts

	Peak Demand (MW)		
DisCo	Low	Medium	High
Abuja	28	45	47
Benin	16	26	28
Eko	83	126	133
Enugu	37	66	69
Ibadan	47	87	93
Ikeja	13	18	19
Jos	14	24	26
Kaduna	19	34	36
Kano	9	17	18
P/Harcourt	38	68	74
Yola	9	17	17
Total	314	530	560

There is a less than 10% percentage point increase per DisCo between the medium and high scenarios. The marginal increase is driven by a 20-percentage point increase in AC ownership between both scenarios. Future research will seek to assess the impact of AC ownership on usage rates, as the usage rates built into the model are based on typical average usage rates for Nigeria.

An increase in customer population will be the key driver for demand in this tariff class. From NERC (2015), the average annual growth rate of R3 and R4 customers is projected at 6%, however these tariff classes only contribute to 0.09%[7] of the total residential customer population. As appliance ownership levels are similar across this

[7] This is the percentage of small and large estates to total residential customers. Using the R3 and R4 customer/estate assumptions employed in this study, this figure increases to 5%.

customer tariff class, the peak demand is expected to remain at similar levels even as socioeconomic conditions improve.

5.4.2 Demand Pattern

In addition to the peak demand, the pattern of demand is also important. The national aggregate residential hourly demand profile for one week is shown in Figure 5-21 for all 3 scenarios. All 3 profiles exhibit a similar pattern as the same data set has been used to model household behaviour across the different locations. However, the difference in hourly magnitude is a function of the scenario appliance ownership and the customer population across the different locations. The simulation of household cooling demand enables the spatial and temporal modelling of the characteristic effect of weather on demand. This allows the analysis of the daily and monthly variations in both distribution networks and aggregate demand data.

The profiles exhibit patterns typical of residential households with 2 diurnal peaks; in the morning and at night. The weekend demand (day 6 and 7) is typically higher than the weekday demand for residential customers, as household members spend more time at home during the weekends (UKERC, 1997). This is opposed to the weekly profile trend for the total network demand, as industrial, commercial and network customers operate on weekdays resulting in higher weekday demand.

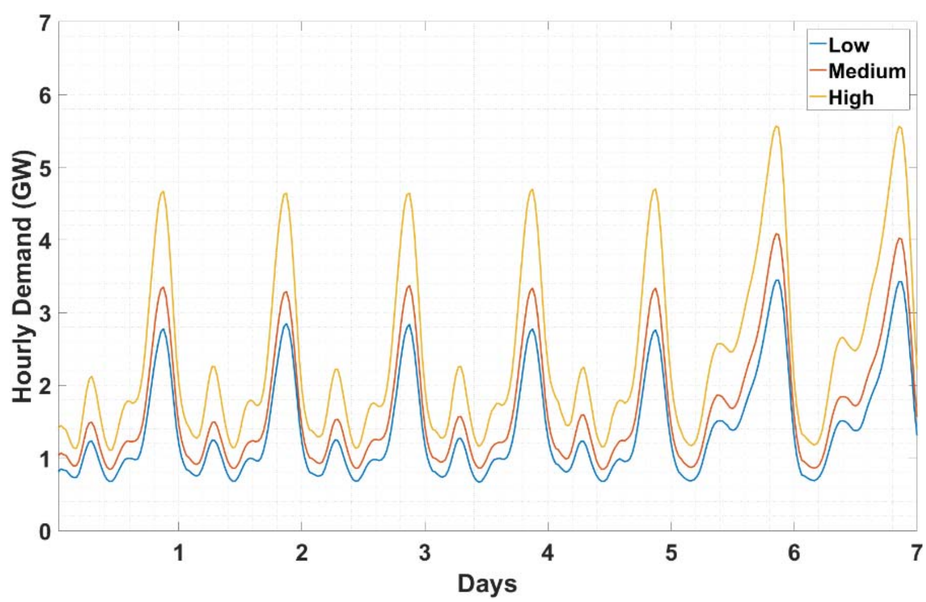


Figure 5-21: Aggregate residential demand hourly profile

Figure 5-22 shows the aggregate residential hourly cooling demand profile. Across the week shown, there are hourly changes in cooling demand in response to hourly temperature changes. For the cooling demand profile, the peak demand occurs in the early morning of day 4 (Figure 5-23), corresponding to increased air conditioning use as a result of the day's warmer temperatures compared to the rest of the week.

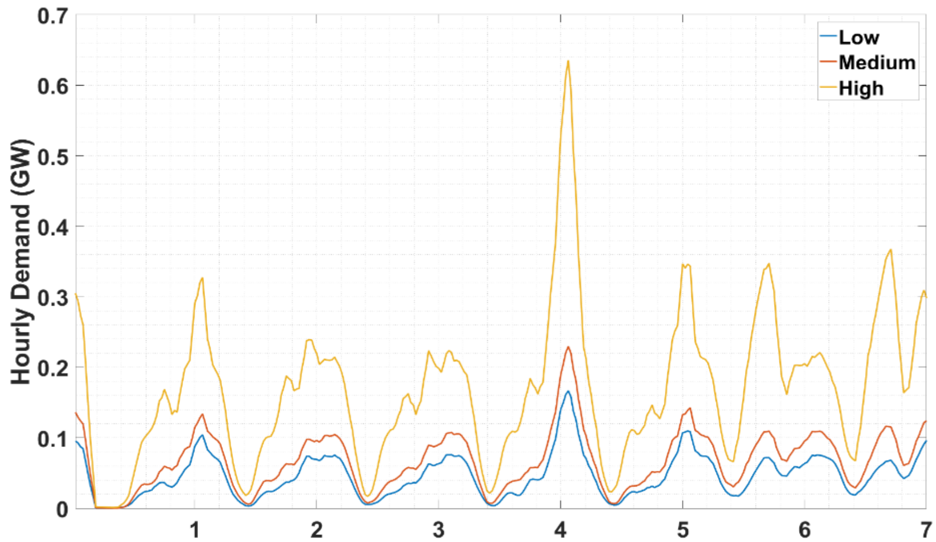


Figure 5-22: Aggregate residential cooling demand hourly profile

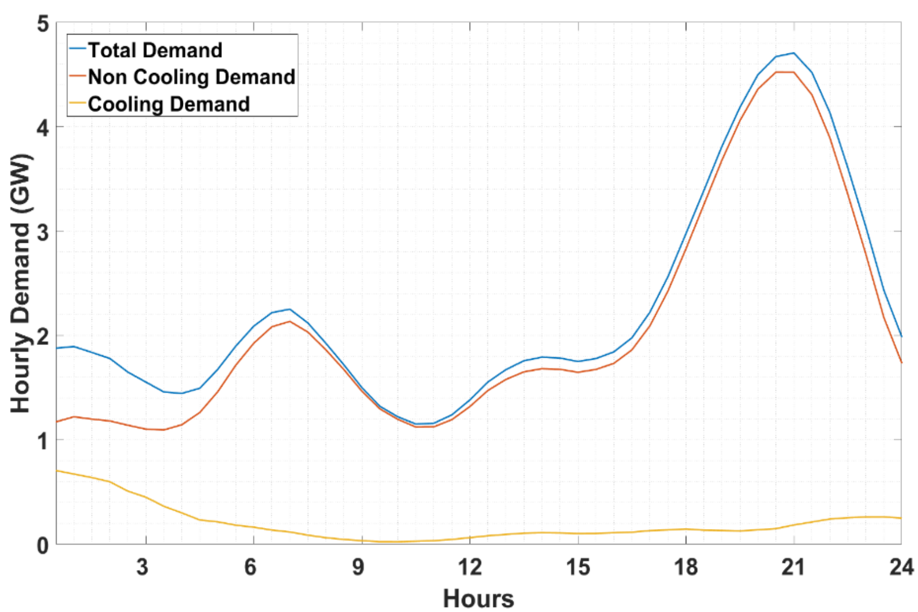


Figure 5-23: Hourly residential demand profile for day 4 (Cooling and non-cooling demand low scenario)

Daily Pattern

The aggregate residential daily peak and cooling peak demand are shown in Figure 5-24 and Figure 5-25 respectively. The annual daily changes in the aggregate peak demand corresponds to the changes observed in the aggregate peak cooling demand, with coincident peaks observed on the same day for both.

The aggregate cooling demand rises in October and peaks in March, and gradually declines till September. This trend follows the seasonal weather pattern in Nigeria, with peak cooling demand observed throughout the dry season, which lasts between October and March.

Dry season midday temperatures are typically warmer than the night temperatures, resulting in higher intraday temperature differentials and increased cooling demand. The day time temperatures during the rainy season are cooler compared to the dry season, resulting in low intraday temperature differential and reduced cooling demand.

In Figure 5-25, greater variability is observed in the high scenario compared to the low and medium scenarios, as a result of higher AC appliance ownership in the high scenario. This translates to Figure 5-24, as the annual variation in the daily peak demand profile in the low and medium scenarios are less distinguished compared to the high scenario.

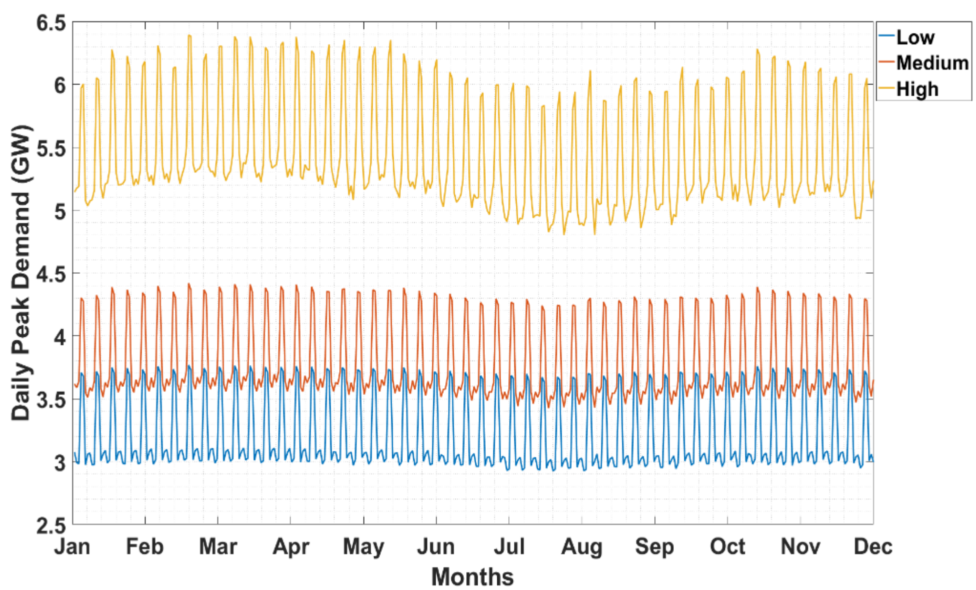


Figure 5-24: Total daily aggregate residential peak demand

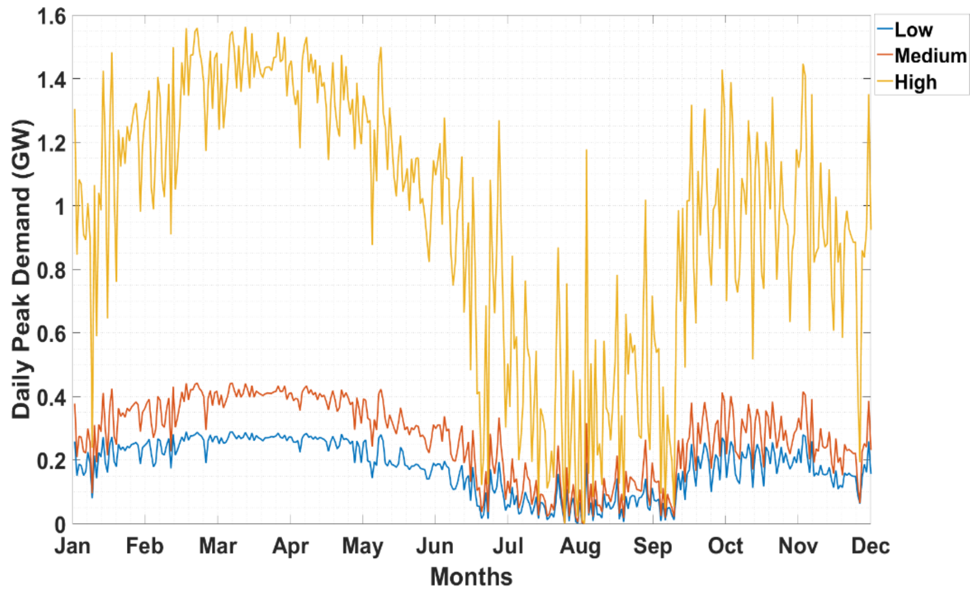
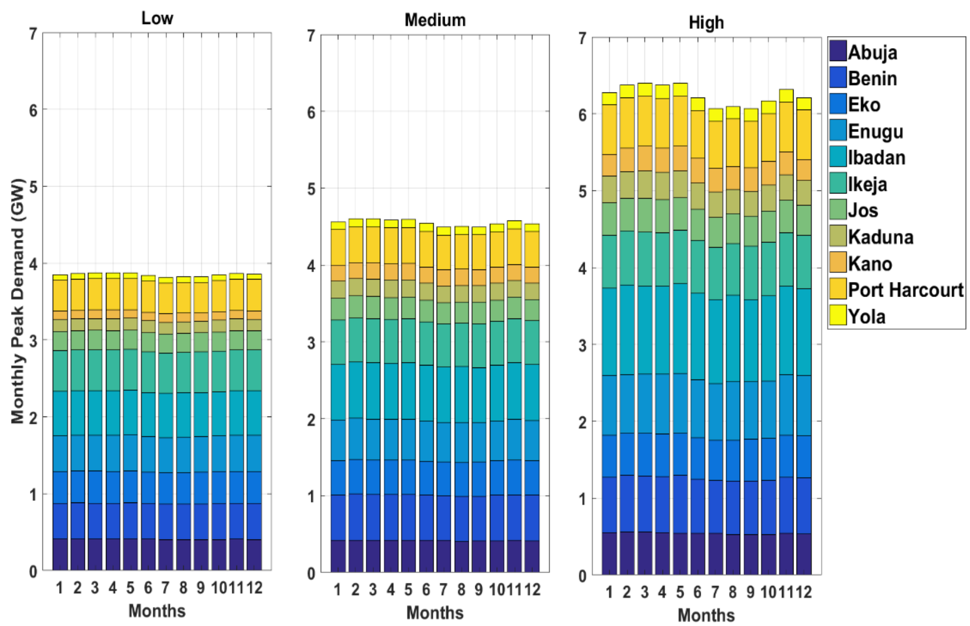


Figure 5-25: Total daily aggregate residential peak cooling demand

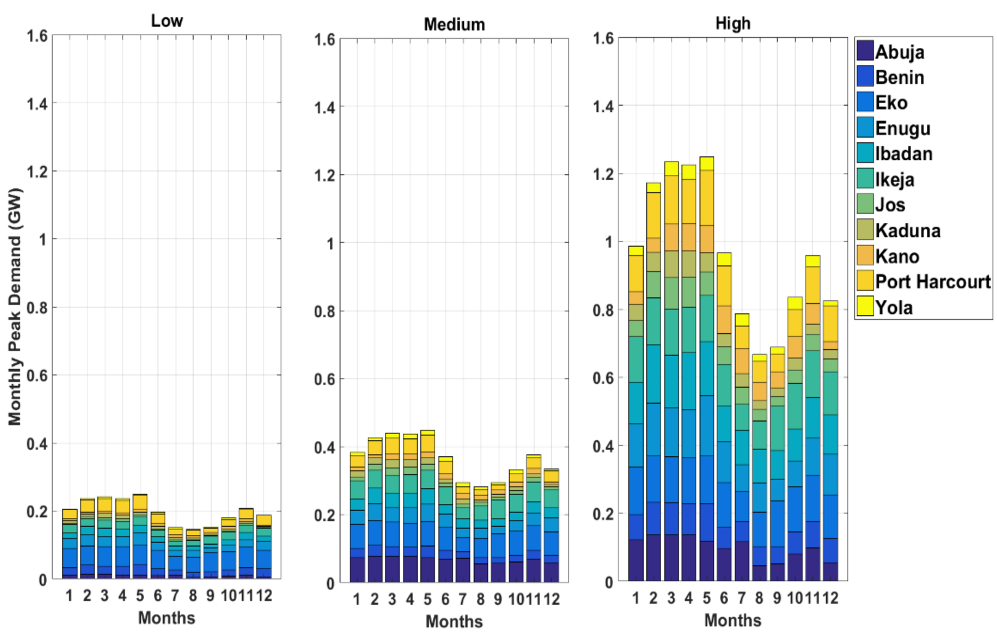
<u>Monthly Load Pattern</u>

In addition to the daily load pattern, an analysis of the annual monthly peak pattern has also been performed. Figure 5-26 shows the national aggregate monthly total peak and cooling demand. Although less prominent in the low and medium scenarios, it can be seen in the high scenario that there are two annual periods of peak demand, with the initial period occurring between February and May, and the second period occurring in November. These spikes are influenced by changes in the monthly peak cooling demand from the DisCos (Figure 5-26b). The annual total peak demand shape becomes more prominent as we move from the low to the high scenario, owing to the effect of increased AC ownership on peak cooling demand. Since the peak cooling demand represents the simulated aggregate cooling demand for each state in Nigeria, it is expected that as AC ownership across the country increases, the national peak demand will exhibit a similar annual pattern.

In order to assess the degree of coincidence in monthly peak cooling demand pattern among the DisCos and the aggregate cooling peak demand, a cross correlation analysis is performed. This analysis is used to assess the influence of the DisCo peak cooling demand on the national aggregate peak cooling demand, and to also highlight DisCos with similar monthly cooling load patterns.



(a)



(b)

Figure 5-26: Aggregate Monthly Peak Demand (a) Total (b) Cooling

Figure 5-27 shows the correlation coefficients of the sum of daily peak cooling demand per month between the pairs of DisCos and the national aggregate cooling demand for the high scenario. The scenario type does not have an effect on this analysis because while cooling demand magnitude varies across the scenarios, the monthly demand pattern remains the same.

At the national level, predictive influence of the DisCos on the national peak aggregate cooling demand is high for all companies with the exception of Kano, and to a lesser degree, Eko and Ikeja (both are in Lagos state). For Eko and Ikeja, this is as a result of the significant reduction in cooling demand in between June and September. There is low coincidence between the monthly peak cooling demand of Kano and the aggregate demand, due to dissimilar weather patterns between the Kano DisCo region and the rest of the country.

While the seasonal onset and daily temperatures vary across the states in the country, bordering DisCos exhibit similar monthly cooling peak demands, while DisCos that are farther apart exhibit lower similarity.

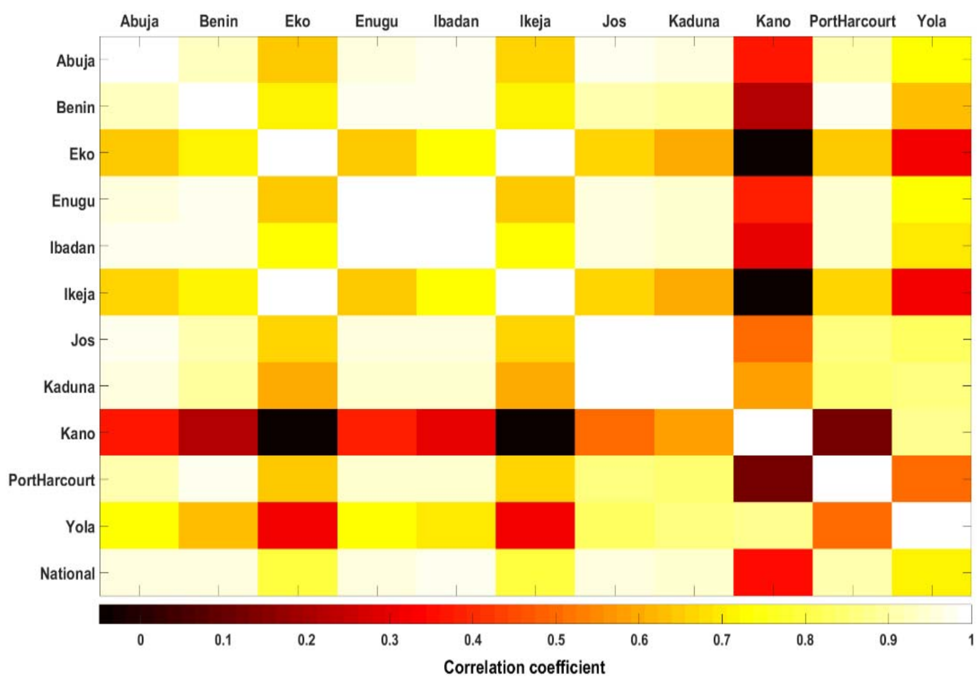


Figure 5-27: Monthly peak demand correlation of the distribution networks

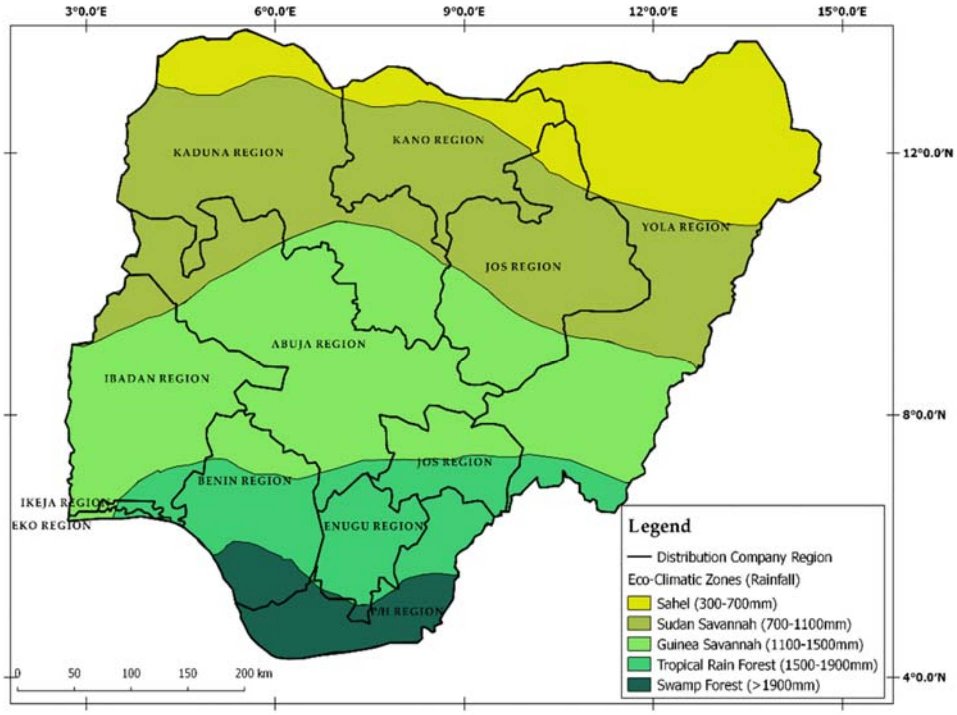


Figure 5-28: Map of Nigeria showing eco-climatic zones

Figure 5-28 shows the eco-climatic zones in Nigeria by DisCo region. For example, Abuja borders Benin, Ibadan, Enugu, Jos and Kaduna, exhibiting higher monthly peak demand correlation. Again, the farther we move away from Eko and Ikeja (both are in Lagos), the poorer the correlation, as indicated by the correlation colour gradient.

The differences in the monthly cooling demand pattern across the distribution networks impacts the aggregate peak demand, as the different DisCos will experience peak demand between February and May, the dry season months, as shown in Figure 5-29.

This influence is dependent on the AC appliance ownership across the distribution networks. In the low scenario, flatter monthly peak profiles are observed for most of the networks, with the exception of Ibadan, Eko, Ikeja, Abuja, Port Harcourt and Benin. In the medium scenario, the monthly peak variation increases but with minimal monthly changes for Kano and Yola. In the high scenario, the highest AC appliance ownership scenario, the monthly variations are more prominent across all the networks.

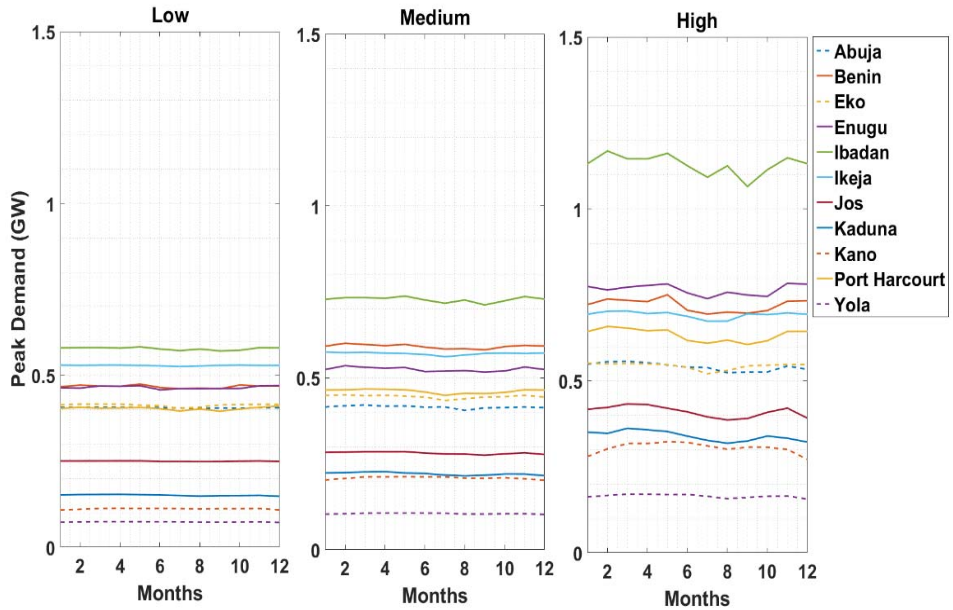


Figure 5-29: Scenario monthly peak demand by DisCo

With increasing appliance ownership from the low to high scenario, the magnitude of the annual peak demand profile for the DisCos increases as discussed in section 5.4.1. Notable changes occur in Benin and Enugu distribution networks.

In the network peak demand ranking, Enugu goes from fourth in the low scenario, to second, in the high scenario. Benin goes from third in the low scenario, to second in the medium scenario and is overtaken by Enugu in the high scenario. Rankings for the other networks remains unchanged.

5.4.3 Load Curves and Load Factor

The simulated aggregate cooling and total load duration curves are presented in Figure 5-30 and Figure 5-31. The generated curves have steep curves owing to the impact of peak cooling demand on total demand. The temperature on the warmest day determines the peak cooling demand, as there is high coincidental usage among households. Usually the warmest temperature hours last for a small portion of the total hours of the year (<2%), therefore in networks with significant cooling demand, this results in a peaky load curve followed by a gradual adoption of a curved gradient (Independent Market Operator, 2014). The load factor for a residential cooling load curve, obtained as the ratio of average energy to peak demand can be used to determine the measure of this peaky characteristic (Koomey, et al., 1989).

Appliances with high load factors (>60%) will yield flatter load duration curves, while appliances with lower load factors will exhibit the peaky characteristic. The average load factor values obtained for the cooling demand curve across the three scenarios compare well to the values obtained for a residential air conditioning load curve shape study for the US (LaCommare, et al., 2002). Load factors for that study have values that range between 14% and 35% for different energy efficiency scenarios.

A significant increase in AC ownership will pose operational and financial challenges for the transmission and distribution systems, as capacity investments to serve peak demand will be underutilized for most of the year, as peak demand will only occur for a small duration of the year. This will also affect system generation, as operationally expensive peak load generators will be required to serve this demand for short periods of the year. The load factor values obtained for the total demand curve, which varies between 37.2% and 38.5%, also compare well to the 38% to 44% range of residential load factors obtained across the four main US regions (Hostick, et al., 2012). Table 5-8 shows the national residential energy and load factor estimates. For the scenario analysis, the effect of increasing appliance ownership across the three scenarios results in changes to the peak magnitude and load curve positions.

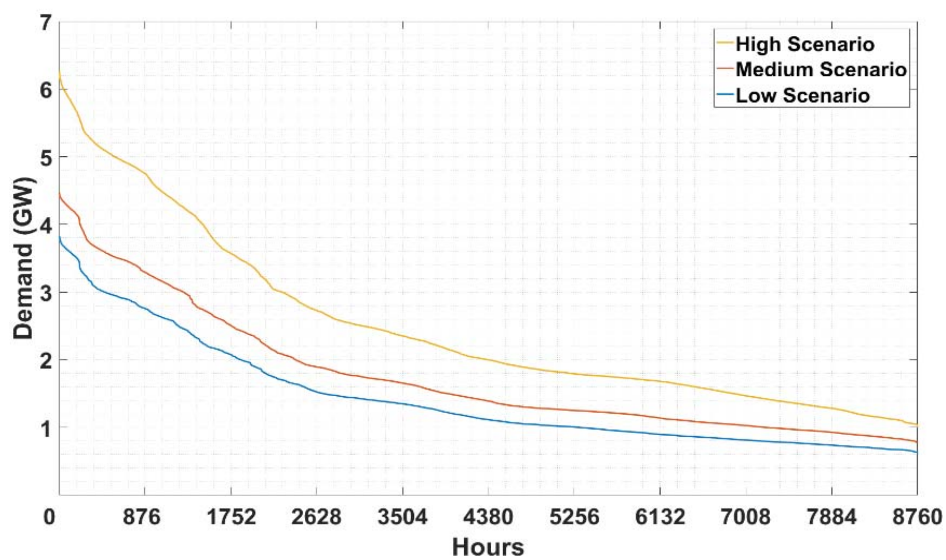


Figure 5-30: Aggregate residential total load duration curves

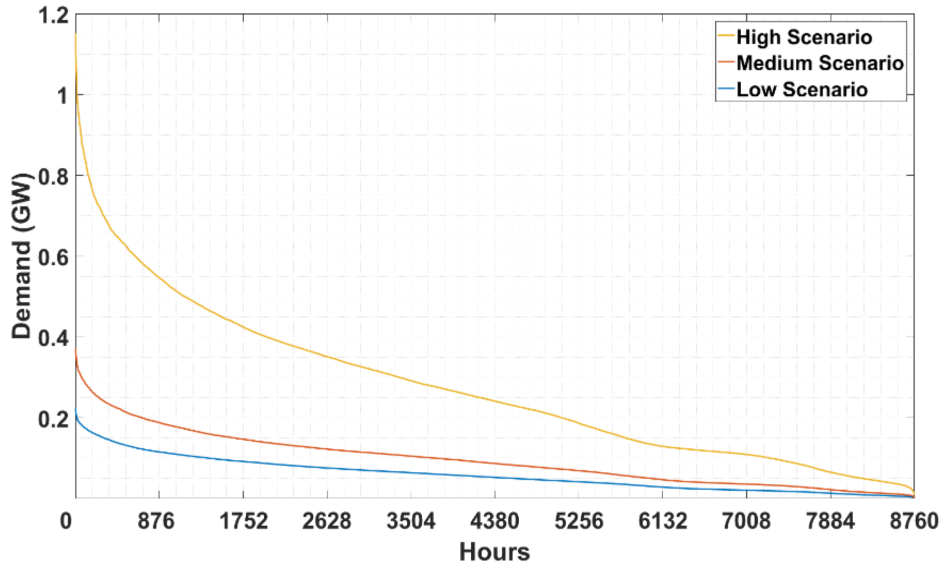


Figure 5-31: Aggregate residential cooling load duration curves

Table 5-8: Aggregate residential energy and load factor estimates

Demand	Scenario	Energy (TWh)	Load Factor (%)
Total	Low	12.5	37.2
	Medium	15.3	37.9
	High	21.9	38.5
Cooling	Low	0.6	23.0
	Medium	0.9	22.5
	High	2.5	20.7

The area under the load duration curve is the energy consumed in that period, therefore any change in the load curve impacts the energy consumed. For both the total and cooling load duration curves, there is an upward shift in the load curve from the low to high scenario due to the increased appliance ownership, which results in higher energy consumption. Table 5-8 shows that total annual energy consumption varies from 12.5TWh to 21.9TWh, and the cooling energy consumption varies from 0.5TWh to 2.4TWh. For the cooling load duration curve, the aggregate effect of increasing AC ownership in warmer regions results in an increase in the electricity demand for cooling. The contribution of cooling energy to the total energy consumed varies from 4% in the low scenario, to 5% and 11% in the medium and high scenarios respectively.

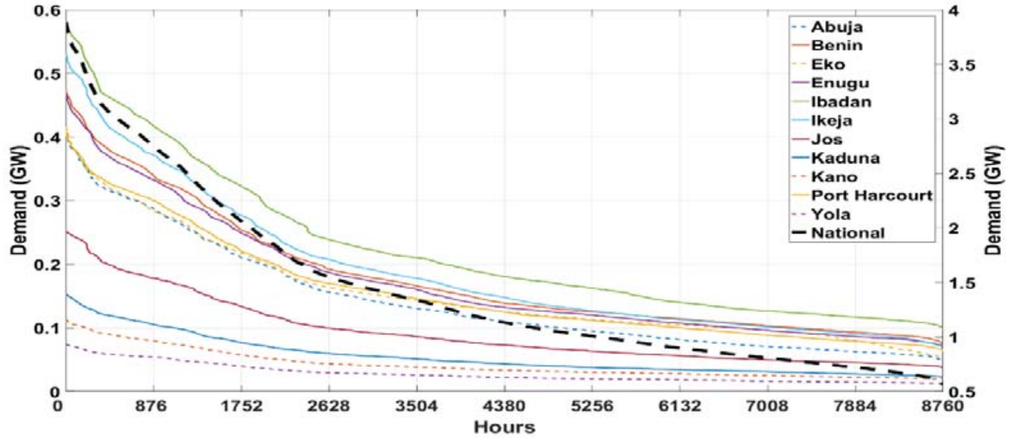
5.4.4 Socioeconomic Impact on Estimates

The impact of the appliance ownership changes for each scenario on total energy consumption in each DisCo is shown in Table 5-9. Appliance ownership impact on the DisCo load curves is shown in Figure 5-32. The right y-axis indicates the total aggregate demand, while the left indicates the DisCo disaggregated demand. The appliance ownership changes at the DisCo level results in increases in peak demand and energy consumed.

Table 5-9: Residential energy estimates by DisCo

	Energy (TWh)			*Scenario Change (%)*		
DisCo	Low	Medium	High	*Low to Medium*	*Medium to High*	*Low to High*
Abuja	1.2	1.3	1.9	*13*	*45*	*64*
Benin	1.6	1.9	2.5	*24*	*29*	*59*
Eko	1.3	1.6	2.0	*20*	*26*	*51*
Enugu	1.5	1.8	2.7	*19*	*49*	*78*
Ibadan	2.0	2.5	3.8	*29*	*52*	*97*
Ikeja	1.7	1.8	2.5	*13*	*32*	*48*
Jos	0.5	0.9	1.4	*16*	*50*	*75*
Kaduna	0.5	0.8	1.2	*59*	*52*	*142*
Kano	0.4	0.7	1.1	*88*	*56*	*194*
Port Harcourt	1.4	1.6	2.2	*16*	*40*	*63*
Yola	0.2	0.4	0.6	*50*	*57*	*135*
Total	12.2	15.3	21.9	*22*	*42*	*74*

With the largest customer population, the R2 tariff class is the significant driver of the change in energy consumption. From the low to medium scenario, the appliance ownership at the state level catches up to the national urban level for states with ownership levels lower than the national urban level or increases by 10% for states above the national urban level. The 22% increase in energy consumption from the low to medium sees substantial influence from Kaduna, Kano and Yola DisCos due to the current low appliance ownership levels in those regions. Using the household survey results, the medium to high scenario sees an average increase of 20% in appliance ownership levels above the current national urban levels for states. With the exception of Eko and Ikeja (Lagos), the increase in energy consumption across the companies is more even, with an average increase of 45%. This is due to Lagos having higher appliance ownership levels than other states in Nigeria.



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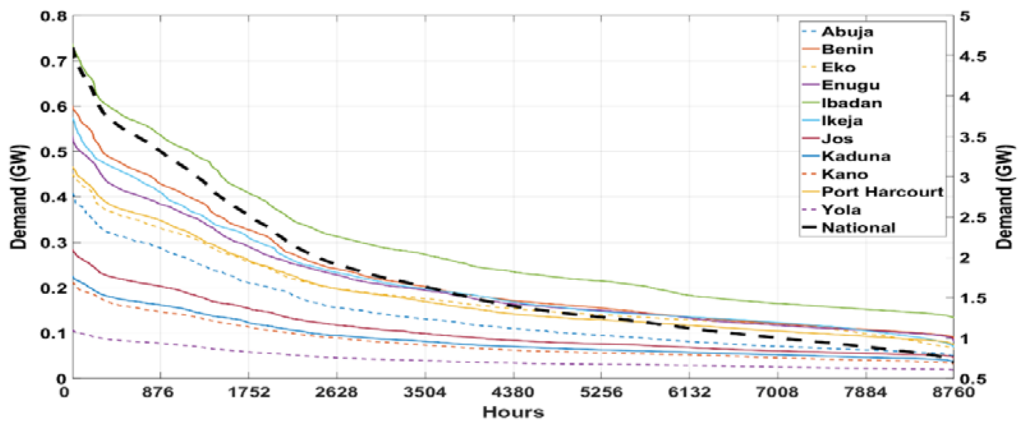

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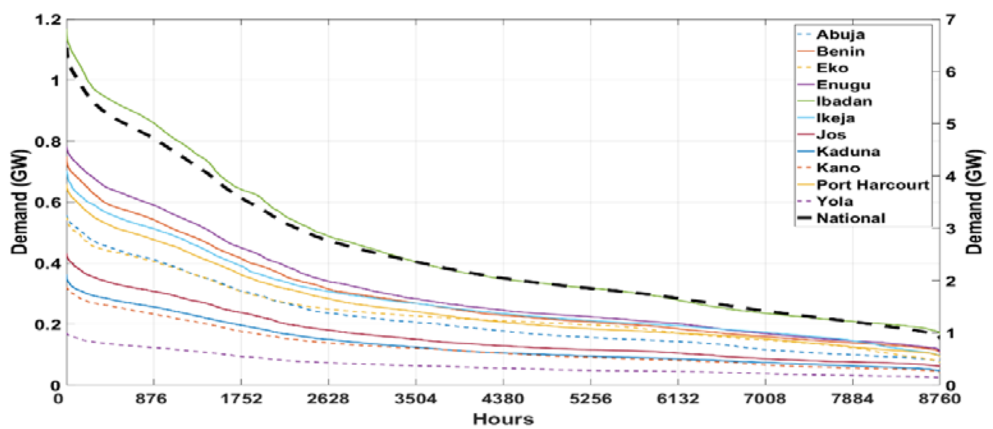


(c)

Figure 5-32: Residential load duration curves (a) Low (b) Medium and (c) High Scenario

The significant increases in energy consumption between the low and high scenario are representative of the current low levels of customer energy consumption. Table 5-10 shows the annual energy consumption per customer for both the total and cooling demand. For instance, the 194%, 142% and 135% increases in total energy consumption from the low to high scenario, represent increases in energy consumption per customer of 1.3MWh/year to 3.6MWh/year, 1.6MWh/year to 3.7MWh/year and 1.6MWh/year to 3.8MWh/year in Kano, Kaduna and Yola respectively. For the high scenario comparison, the 2013 average household energy consumption for the UK was 3.6MWh (Intertek, 2013).

Table 5-10: Annual energy consumption per customer (kWh)

	Total Demand			Cooling Demand		
DisCo	Low	Medium	High	Low	Medium	High
Abuja	2,648	2,717	4,024	39	129	452
Benin	2,364	2,920	3,764	86	97	296
Eko	4,203	5,027	6,339	525	646	1,242
Enugu	2,122	2,532	3,784	72	108	321
Ibadan	1,841	2,377	3,625	36	71	284
Ikeja	3,238	3,643	4,794	145	322	751
Jos	1,982	2,299	3,459	21	73	300
Kaduna	1,562	2,477	3,777	48	101	331
Kano	1,250	2,353	3,669	48	110	484
Port Harcourt	2,436	2,830	3,976	116	140	457
Yola	1,648	2,469	3,877	57	166	499
Total	2,299	2,815	4,008	95	155	443

As the appliance ownership increases, the energy consumed per customer also increases. For the total demand, increasing the appliance ownership from the low to high scenario shows that the average energy consumed per customer varies from 2.3MWh/year to 4MWh/year. For the cooling demand, the average energy consumed per customer varies from 95kWh/year to 443kWh/year. The highest energy consumption per customer is seen in Eko, Ikeja and Abuja, driven by stronger appliance ownership rates and a larger population of R3 and R4 customers.

While increases in appliance ownership levels will see increased energy consumption across the companies, the distribution networks most sensitive to changes in socioeconomic conditions in their regions are Kaduna, Kano and Yola. Overall, increasing the AC ownership from the low to high scenario shows that the increases in energy consumed varies from 22% to 74%.

Cooling Demand

The impact of increasing AC ownership is assessed by analysing scenario changes in the annual cooling energy consumption. Table 5-11 shows the average national AC appliance ownership rate used for each tariff class.

Table 5-12 shows annual cooling energy consumption by tariff class. The impact at DisCo level is summarised in Table 5-13.

Table 5-11: Average AC saturation by tariff class (%)

Tariff Class	Low	Medium	High
R1	1	3	5
R2	3	5	28
R3 & R4	40	60	80

Table 5-12: Annual residential cooling energy by tariff class

	Annual Cooling Energy (GWh)			*Scenario Change (%)*		
Tariff Class	Low	Medium	High	*Low to Medium*	*Medium to High*	*Low to High*
R1	2	3	6	*63*	*116*	*253*
R2	305	523	1,971	*71*	*277*	*546*
R3 & R4	211	319	439	*51*	*38*	*108*
Total	518	845	2,416	*63*	*186*	*367*

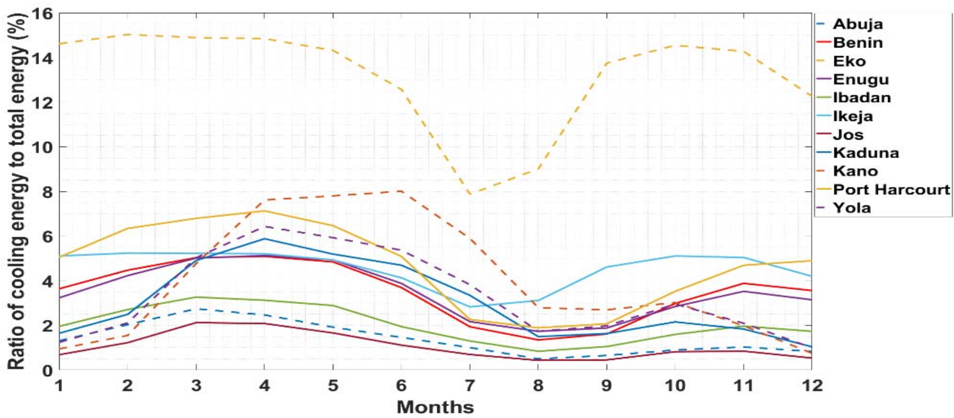
Table 5-13: Annual Residential cooling energy by DisCo

	Annual Cooling Energy (GWh)			*Scenario Change (%)*		
DisCo	Low	Medium	High	*Low to Medium*	*Medium to High*	*Low to High*
Abuja	18	60	211	*234*	*250*	*1,071*
Benin	57	64	196	*13*	*206*	*245*
Eko	169	207	399	*23*	*92*	*136*
Enugu	51	76	228	*49*	*198*	*346*
Ibadan	38	75	302	*98*	*300*	*691*
Ikeja	74	164	383	*122*	*133*	*418*
Jos	8	30	122	*255*	*308*	*1,350*
Kaduna	15	31	102	*113*	*227*	*596*
Kano	14	33	143	*129*	*339*	*906*
Port Harcourt	65	78	256	*20*	*227*	*294*
Yola	9	25	75	*189*	*201*	*771*
Total	518	844	2,416	*63*	*186*	*367*

Increases in AC saturation have a corresponding effect on energy consumption as shown by the energy increments to the changes in ownership level. Sailor & Pavlova, (2003) showed the climate change influence on the ownership of residential ACs in twelve cities across four US states. Cities with the least AC ownership had the most significant increases in AC energy consumption. AC ownership increases of 9%, 5%, and 9%, resulted in AC energy consumption increases of 60%, 49% and 44%, in Buffalo, New York; San Francisco, California and Rochester, New York respectively. While temperature is held constant in this current study, results from this research correspond with those findings as shown by the growth in energy consumption due to increases in AC ownership at tariff class level. A 4%, 25% and 40% increase in AC ownership across from the low to high scenarios, sees an increase in AC energy consumption of 253%, 546% and 108%, in R1, R2 and the R3&R4 tariff classes respectively. These increases are reflective of potential increase in demand given the temperature levels across the country. While significant increases in cooling energy consumption are shown, reasonable estimates of the average consumption per customer have already been given in Table 5-10.

While the wealthier and more populated regions of Eko, Ikeja and Ibadan have the highest annual energy demand; Abuja, Jos, and Kano experience significant increases in per capita energy consumption from the low to high scenario, driven by the influence of warmer temperatures and AC ownership on cooling demand.

The scenario contribution results of cooling energy demand as a percentage of total monthly energy demand for each DisCo are shown in Figure 5-33. From the low to high scenario, increases of 1,307%, 1,043% and 907%, translate to increases in cooling energy consumption per customer of 21kWh/year to 300kWh/year, 39kWh/year to 452kWh/year and 48kWh/year 484kWh/year for Jos, Abuja and Kano respectively. It must be noted that while significant increases in energy consumption accompany the AC ownership growth, this research has maintained the same thermal comfort level in each scenario analysis as shown in Chapter 4. Overall, increasing the AC ownership from the low to high scenario shows that the increases in energy consumed varies from 63% to 367%. Future work will explore the impact of varying the thermal comfort levels based on state comfort preferences on aggregate electricity demand.



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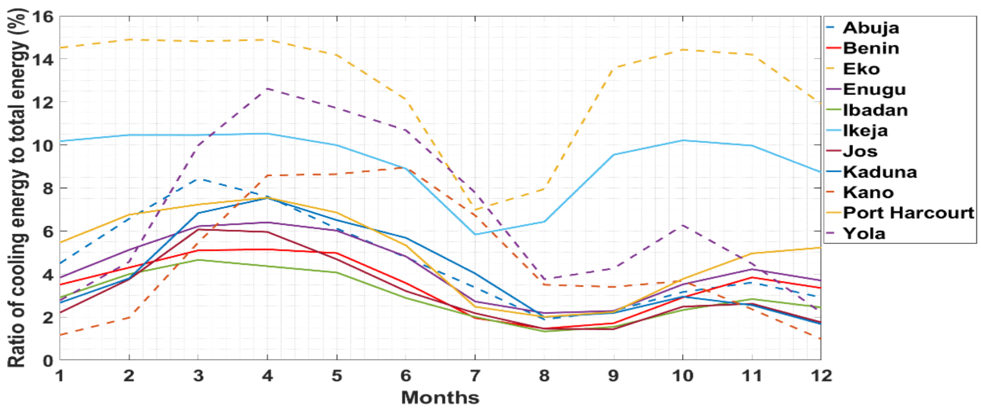

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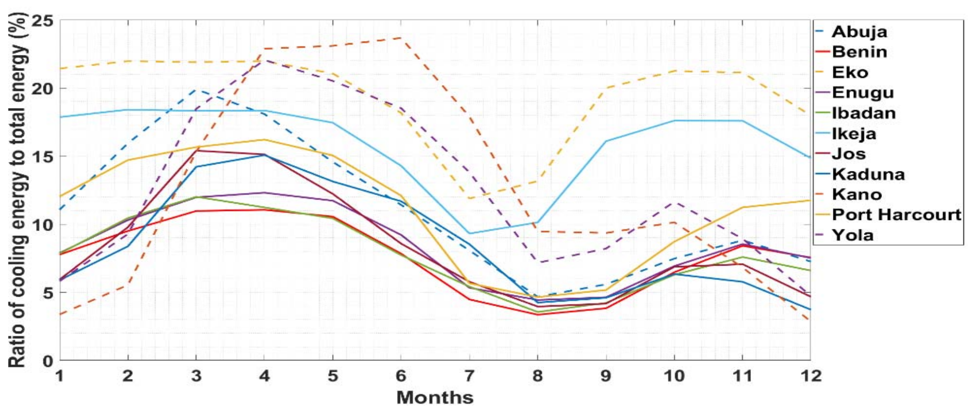


(c)

Figure 5-33 Monthly cooling energy contribution (a) Low (b) Medium and (c) High Scenario

While the shape of the annual profile remains the same across all scenarios, increased AC ownership from the low to high scenario sees an increase in the monthly contribution of cooling energy to total energy for the distribution companies. While the rest of the companies have peak demand between February and April, the peak demand in Kano occurs between April and June. This is due to the Kano region experiencing a later rainy season onset compared to other regions, hence a longer dry season spell. There is a reduction in demand across all companies between July and August. With peak demand occurring over the dry season months, the annual AC contribution to total energy demand is highest in Lagos (Eko and Ikeja), Kano and Yola, and least in Ibadan, Jos and Benin.

5.4.5 Weather Data Performance

To assess the performance of the model in responding to hourly changes in geospatial weather data, the daily aggregate cooling demand is analysed for 4 locations using 2014 to 2016 MERRA-2 data. The 2014 to 2016 analysis allows for a seasonal weather trend comparison for each location, and to assess the predictive consistency of the annual temperature data. The results in Table 5-14 show the aggregate mean daily energy consumption in each location. Figure 5-34 to Figure 5-37 show the mean cooling daily energy consumption in Abuja FCT, Enugu, Kano, and Lagos states respectively.

Cooling energy consumption is higher during the dry season compared to the rainy season due to the daily temperature differential, which is the difference between the minimum daily temperature and maximum daily temperature. In Abuja FCT and Enugu, peak cooling demand occurs between February and March before the onset of the rainy season in April. The temperature difference between both locations sees a dry season consumption variance of between 5.6-6.8kWh for Abuja FCT, and between 2.1-3.9kWh for Enugu. In Kano, peak cooling demand occurs between May and June due to a longer dry season. Lagos sees consistent cooling demand with an exception between the months of May and September, during the midpoint of its rainy season. The geospatial temperature effect on cooling energy consumption sees a dry season consumption variance of between 4.9-5.3kWh for the coastal state of Lagos and between 5.3-6.5kWh for the northern arid location of Kano. The dry season sees large daily variances in cooling demand, but this gradually diminishes during the rainy season. This is particularly evident in Lagos, which has the longest rainy season duration of the 4 locations, and lower daily variances in cooling demand. With the lowest inter-seasonal change in temperatures, Lagos has the highest daily energy consumption (4.0-4.2kWh) of the studied locations.

The annual demand profiles in each location follow the same pattern for the 2014 to 2016 weather data, revealing a consistency in predictive trend of the MERRA-2 data. From 2014 to 2016, there is a yearly increase in dry season energy consumption, with the 2016 dry season yielding the highest cooling energy consumption across all the locations.

Table 5-14: Cooling energy consumption by selected locations

		Mean daily cooling energy consumption (kWh)		
Locations	**Season**	**2014**	**2015**	**2016**
Abuja FCT	Annual	3.5	3.7	3.4
	Dry	5.6	6.2	6.8
	Rainy	2.1	2.1	1.8
Enugu	Annual	1.6	1.7	2.1
	Dry	2.1	2.5	3.9
	Rainy	0.9	1.0	1.0
Kano	Annual	2.8	2.8	3.0
	Dry	5.6	5.7	6.5
	Rainy	2.0	2.2	2.5
Lagos	Annual	4.2	4.2	4.0
	Dry	5.0	4.9	5.3
	Rainy	2.9	2.6	2.6

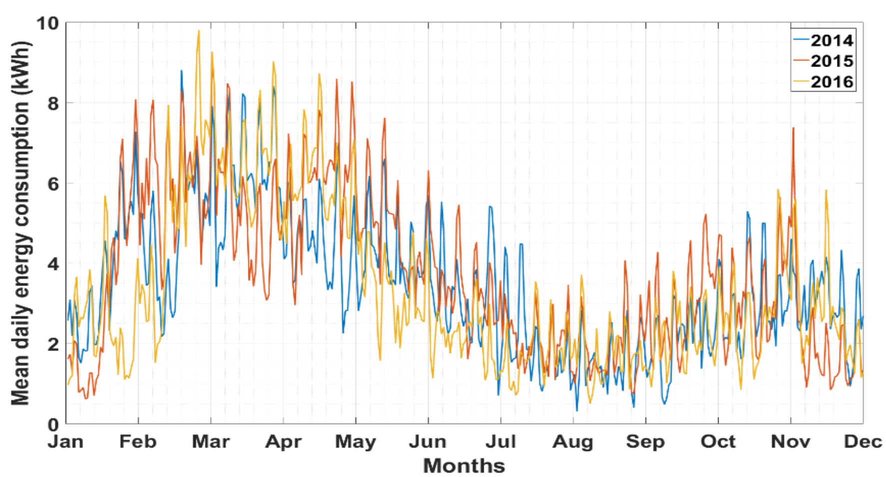


Figure 5-34: Abuja daily cooling energy consumption

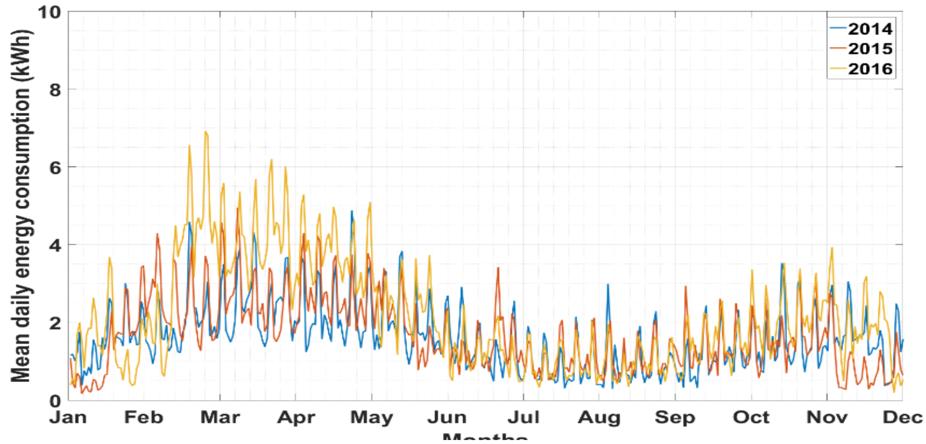


Figure 5-35: Enugu daily cooling energy consumption

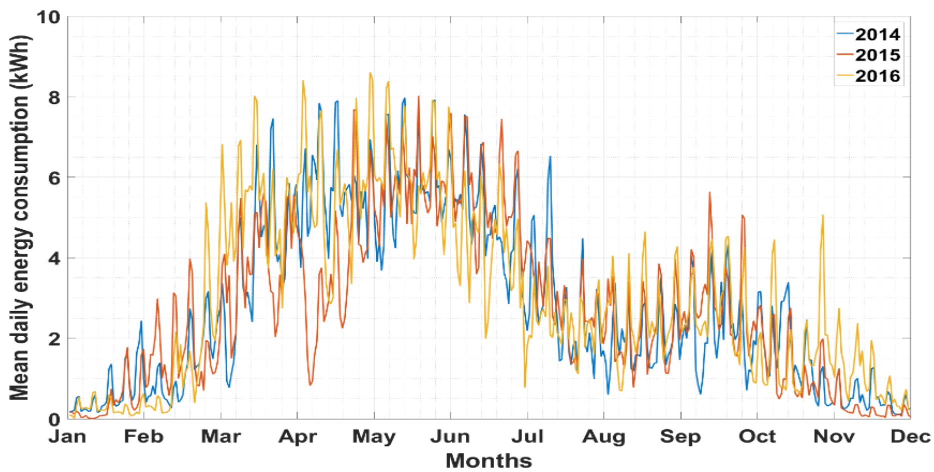


Figure 5-36: Kano daily cooling energy consumption

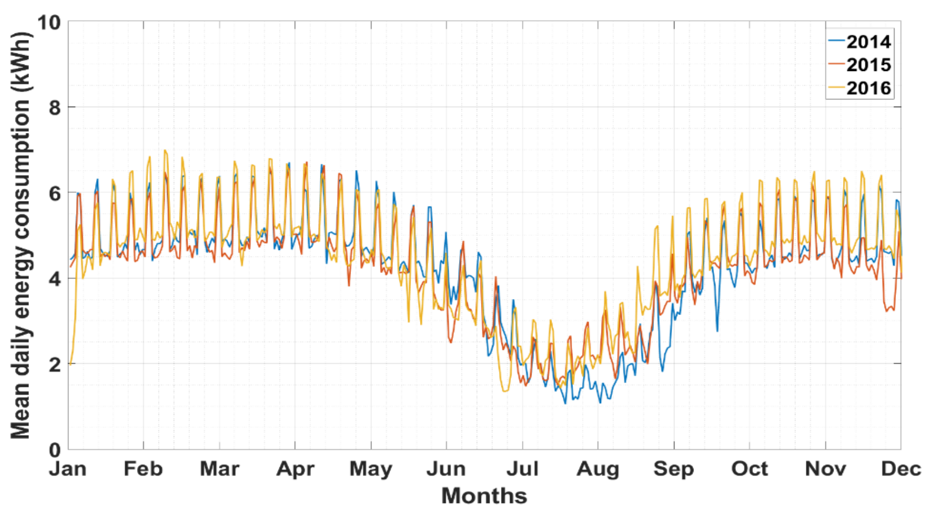


Figure 5-37: Lagos daily cooling energy consumption

For the rainy season, the annual trend is less defined, as the 2016 rainy season data does not produce the highest energy consumption in Lagos and Abuja FCT. Comparing the 2014 and 2015 annual daily energy consumption to that of 2016 yields a range of -1 to 5% across all four locations, which is acceptable for this analysis.

The impact of the MERRA-2 temperature prediction bias on cooling energy consumption was also analysed. This was assessed by reducing the model input hourly temperatures by 1°C based on the MBE analysis from section 5.2.1. While underestimations occur in the maximum daily temperatures, with overestimations of minimum daily temperatures in the MERRA-2 data, the temperatures are reduced to assess the impact on the total cooling demand. The cooling energy results are presented in Table 5-15. The reduction of temperature results in a decrease in cooling energy consumption for all scenarios, as the total number of hours in a year when cooling is required is reduced. For example, the CDD for Abuja FCT at a base temperature of 24°C reduces by 32% from 1488hours to 1127hours, for a 1°C decrease in hourly temperatures.

Table 5-15: Cooling energy temperature bias

	Annual Energy (TWh)		
	Low	Medium	High
Temp °C			
Cooling	0.5	0.8	2.4
Total	12.2	15.3	21.9
(Temp -1) °C			
Cooling	0.4	0.6	1.8
Total	11.7	15.0	21.1

The hourly temperature reduction sees the cooling energy reduce from between 0.5-2.4TWh for the initial condition to between 0.4-1.8TWh when bias corrected, with an average reduction of 26% across the scenarios. The effect of the temperature decrease on total energy consumption sees an average reduction of 4% across the scenarios. The decrease in hourly temperature has a minor impact on the total energy consumption due to the low contribution from cooling energy as a result of AC ownership rates. The impact of temperature changes on total energy consumption is significantly affected by the ownership rates of weather dependent electrical equipment (Sailor & Pavlova, 2003).

5.4.6 Comparison with similar studies

The residential peak demand estimates obtained from this research are compared to a 2008 study undertaken by Power Holding Company of Nigeria (PHCN), the defunct power utility company of Nigeria. In that study, the peak demand estimates for each DisCo was obtained by employing the sigmoid growth curve (s-curve) method. The s-curve method models the pattern of growth of any quantity, from a period of low acceleration, to medium and high, before decelerating until no further growth is observed. The estimates used for that study were the residential specific energy consumption per capita and electrification ratio; this was obtained from the measured energy sold by each DisCo, residential customer population of their coverage states and the population of their coverage states. Peak demand was then estimated using an assumed load factor, similar to the energy load factor ADMD estimation method described in Chapter 2. The 2015 results of the PHCN study are compared with the 2015 values for this study in Table 5-16.

Table 5-16: Demand Analysis: Current Research vs PHCN Study

	Scenario Demand Estimates (MW)					
	Current Research			PHCN Study		
DisCo	Low	Medium	High	Low	Medium	High
Abuja	206	380	559	402	438	553
Benin	476	602	751	458	508	657
Eko	423	458	555	385	436	480
Enugu	471	537	789	439	513	595
Ibadan	586	745	1,175	451	522	616
Ikeja	531	577	704	519	546	602
Jos	83	274	434	218	251	280
Kaduna	155	230	362	316	354	454
Kano	114	213	324	204	236	265
P/Harcourt	412	470	662	242	274	301
Yola	75	107	172	94	100	110
Total	3,533	4,592	6,485	3,732	4,183	4,917

One of the major drawbacks of the PHCN study is the use of energy sold as an indicator for the growth curve, as the energy sold is constrained by generation supply and limited by frequent power outages resulting from load shedding. However, the current research aims to estimate the electrical demand of all residential customers under constant power supply conditions. While the PHCN study assumes the same growth rate for all residential customers, the current research is able to estimate the peak demand for each customer tariff class based on appliance ownership penetration allowing the assessment of the sensitivity of each customer group to the impact of electrical appliance ownership due to changing socioeconomic conditions. The PHCN study also assumed a constant energy use per capita, while this current research includes a weather component in its model to explore the dynamic relationship between electricity demand and weather. Consequently, it is expected that as well as daily variations in the peak demand, monthly variations should be observed as well.

While both the low and medium scenario estimates are broadly comparable for both studies, the high scenario sees a significant difference in peak demand as a result of higher energy per capita estimates used in the current research. The low scenario for the current research, which uses NBS state level appliance ownership data, projects 5% lower peak demand than that of PHCN. The inclusion of unelectrified respondents in the NBS survey negatively affects the appliance ownership data and the resultant demand in the low scenario. In the medium scenario, appliance ownership for the states have caught up to the national urban level. With a higher electrification among urban respondents, appliance ownership levels are higher, translating to a higher energy consumed per capita, and an increase in overall peak demand. The medium scenario peak demand value for this study is 10% higher than the PHCN study. For the high scenario, the household survey data, which was restricted to only electrified customers, translates to a much higher energy consumption per capita than that used in the PHCN study and a large in peak demand. The high scenario peak demand value for this study is 32% higher than the PHCN study.

Among the distribution companies, there appears to be more significant differences for Ibadan and Kaduna. This could be as a result of a difference between the actual appliance ownership rates and those captured in the national survey for those regions.

From the above analysis, given the broadly comparable demand estimates to that of a previous state sponsored study and the sensitivity of peak demand to energy consumption per capita driven by national socioeconomic and forecasted ambient conditions, the methodology employed in this research is considered reasonable to estimate the residential electricity peak demand for Nigeria.

5.5 National Peak Demand Estimates

To determine the total peak demand estimates for Nigeria, non-residential sector demand estimates from 2009 PHCN study of the Nigerian electricity network are employed (Power Holding Company of Nigeria, 2009). These estimates are based on an econometric growth analysis of the energy per sectorial customer; derived from the distribution network sales to each sector in the year of study, and the influence of population on energy use, obtained as correlation between residential and sectorial energy use. The short-term duration of the study means annual variations to energy use were not factored in, and as such there was no treatment of the potential influence of weather on sectorial energy consumption. The residential peak demand estimates are presented in Table 5-17.

Table 5-17: Residential Peak Demand Comparison

Study	Peak Demand (GW)
Residential - Low	3.8
PHCN – 2015 Low	3.7
Residential - Medium	4.5
PHCN – 2015 High	4.9
Residential - High	6.4
PHCN – 2020 Medium	6.2

Due to the relationship between sectorial energy use and residential energy used in the PHCN study, the sectorial energy estimates have been selected by choosing the peak demand estimates of the year in which the residential energy estimates of the PHCN study closely match the results of this study. Based on the correlation approach employed in the PHCN study, the sectorial peak demand estimates obtained by using this matching criterion represent the sector peak demand values that best correspond to this research's residential peak demand estimates.

Table 5-18 shows the non-residential sector peak demand and the percentage contribution of each sector. Street lighting estimates have been included in the commercial and industrial peak demand estimates. The relative contribution of each DisCo to the total non-residential peak demand is the same in each scenario. Ikeja (20%), Eko (14%) and Ibadan (12%) contribute the highest values of peak demand for the non-residential sector, driven by the volume of commercial and industrial activities within those networks (Figure 5-38).

Table 5-18: Non-Residential Sector Energy Input Data

Parameter	Unit	Low	Medium	High
Peak Demand	GW	2.1	2.6	3.5
Sector Contribution	*(%)*			
Commercial		*31*	*33*	*30*
Industrial		*57*	*56*	*59*
Special		*12*	*11*	*11*

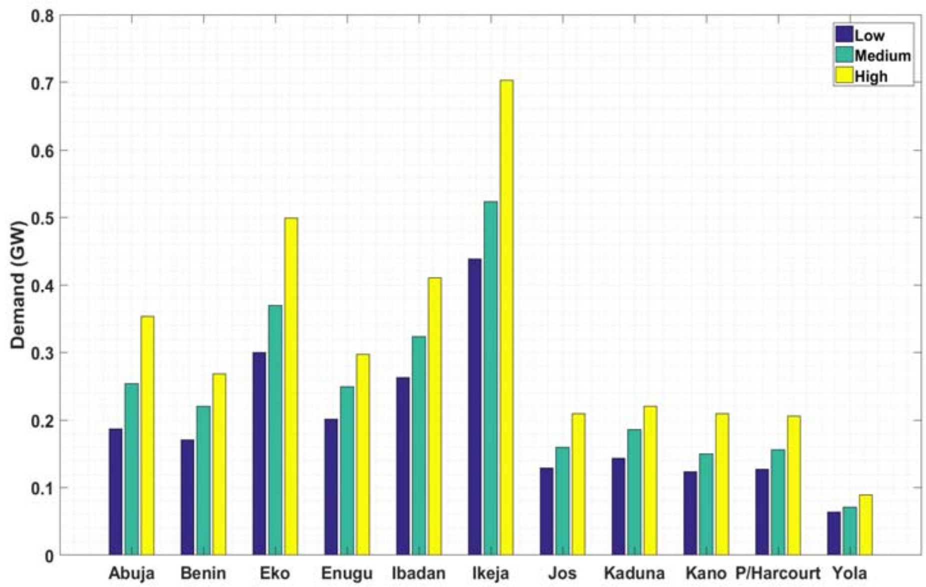


Figure 5-38: Non-Residential Sector Demand by DisCo

Load profiles generated from that study are then applied to the peak demand estimates in each scenario and added to the residential peak demand estimates to obtain the aggregate distribution peak demand profile. Load profile construction is performed at the DisCo level, and then aggregated to obtain the aggregate distribution demand profiles. Industrial loads connected directly to the transmission network have also been disaggregated based on DisCo location. Figure 5-39 to Figure 5-40 show the daily load profiles for the industrial and commercial sectors. The daily industrial load profile is used for both weekdays and weekends, with the assumption that the level of industrial activities remains the same throughout the year.

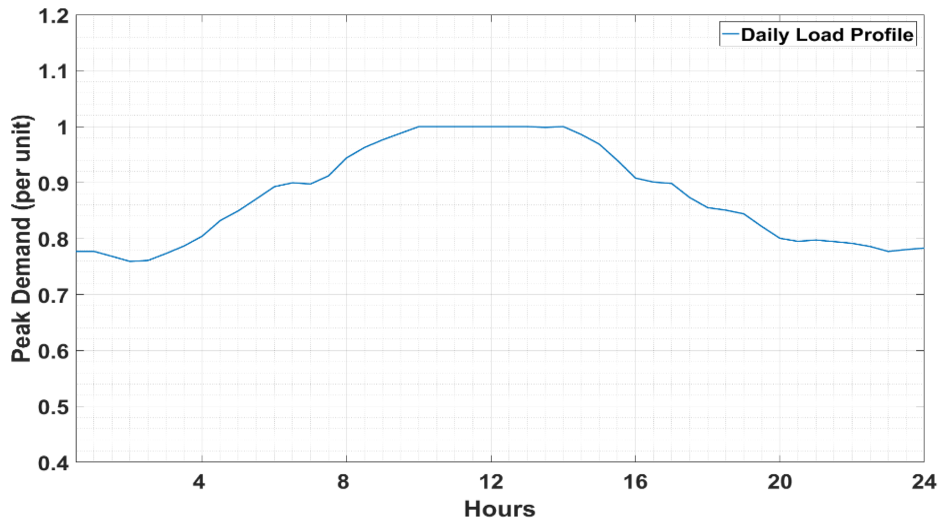


Figure 5-39: Industrial Sector Daily Load Profile

The commercial load profile is applied to special customers as the nature of activities between both sectors are similar. The commercial and industrial load profiles show the patterns expected of those sectors, with a gradual early morning pickup, an afternoon peak and a late evening decline.

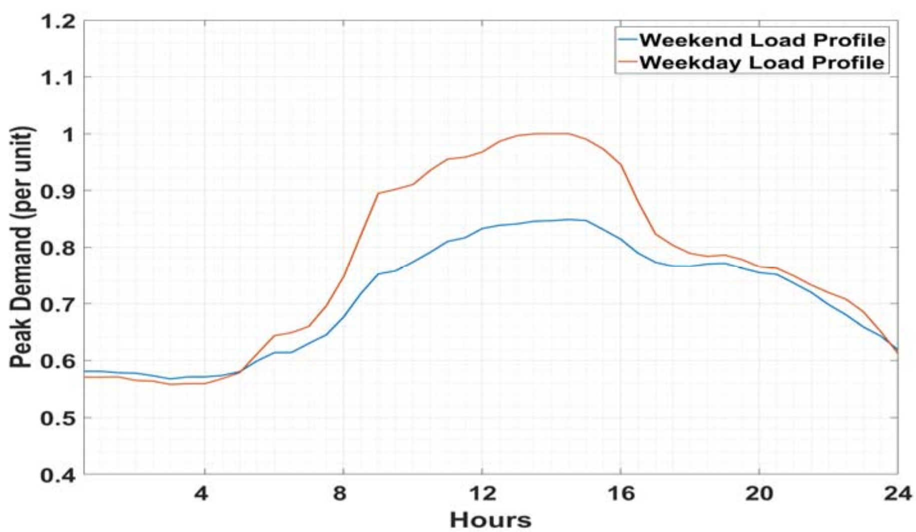


Figure 5-40: Commercial Sector Daily Load Profile

Figure 5-41 shows a one-week snapshot of the aggregated sectorial peak demand. The profiles show a combination of the influence of domestic demand and non-domestic demand, with an early morning pick up, midday demand spike due to non-domestic sector activities and a late evening peak from household demand.

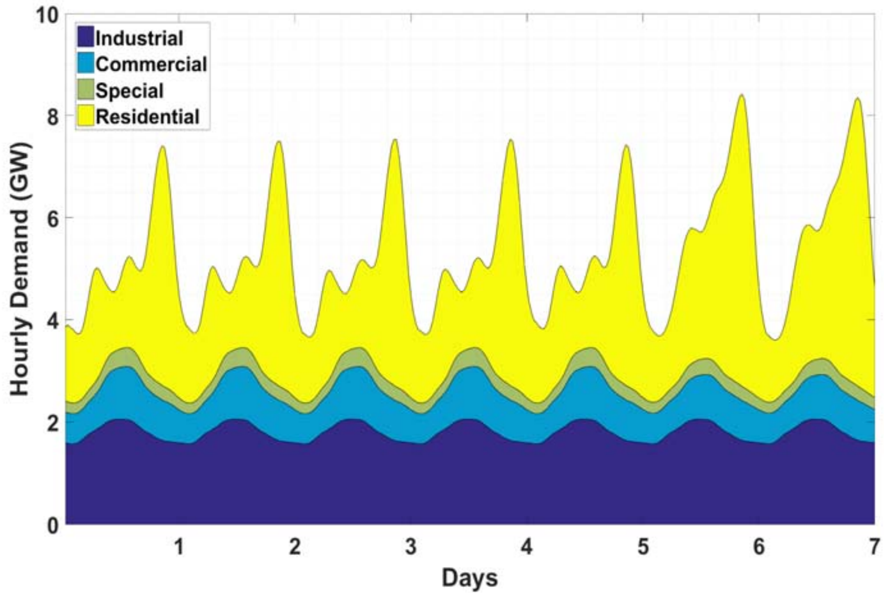


Figure 5-41: Total System Hourly Demand Profile – High Scenario

The non-simultaneous peak demand estimates are shown in Table 5-19. The non-simultaneous peak demand is the sum of the individual maximum demand of the distribution companies. The results are compared to the peak demand estimates for each DisCo (TCN, 2017).

Table 5-19: Scenario Peak Demand by DisCo

Non-Simultaneous System Peak Demand (MW)				
	Scenario			TCN Estimate
	Low	Medium	High	
DisCo				
Abuja	552	578	832	762
Benin	605	771	956	1,223
Eko	649	739	941	1,350
Enugu	624	726	1,013	1,026
Ibadan	786	989	1,488	1,285
Ikeja	871	982	1,253	1,215
Jos	351	408	594	399
Kaduna	263	370	529	602
Kano	209	328	485	708
Port Harcourt	508	587	816	948
Yola	122	160	238	279
Total	5,541	6,636	9,143	9,801

The estimates have been obtained by aggregating measurement results of substation feeders at the 33kV and 11kV level in each DisCo. Similar measurement campaigns in regions prone to load shedding employ extrapolation in the data analysis to account for periods of missing data, which can lead to demand overestimation (Power Holding Company of Nigeria, 2009). Of the three scenarios analysed, the high scenario estimate is most comparable to the measured peak demand estimate for Nigeria, with a difference of 6.7%. This difference can be attributed to the estimation bias of non-domestic peak demand in the PHCN study used in the demand aggregation and the customer allocation by state discussed in section 5.1.3. Underestimation is notably observed in Benin, Eko, Kano and Yola, as the non-domestic demand used in the model for these networks are potentially lower than the actual. For Jos, the domestic customer allocation has included customers from states in neighbouring regions, thereby overestimating its demand. The differences between the measured estimate and the low scenario, and the measured estimate and medium scenario, are 44% and 32% respectively. This can be explained by the socioeconomic data used for estimating domestic demand in both scenarios. The inclusion of unelectrified customers in the NBS survey dampens the appliance ownership rate, thereby reducing the energy consumed per customer. It must also be noted that recorded peak demand for Nigeria is 4.9MW meaning that 50% of the demand is currently suppressed (TCN, 2017). While this model produces a good representation of the system peak demand, variances between model output and the current demand reveal the need for an updated non-domestic peak demand study for Nigeria. An appliance ownership survey targeted at only electrified customers is also required.

The load duration curves obtained for the total demand are shown in Figure 5-42. The peak demand magnitude in each scenario defines the curve position on the plot in a descending order from the high to low scenario. The 2-week simulation of non-cooling domestic demand causes the spikes seen on the load curve due to the combination of a limited range of distribution in appliance power ratings and household appliances. This effect is acceptable for this analysis due to the benefit of a reduced computational burden afforded by a shorter simulation window for the non-cooling domestic demand.

A summary of the energy consumption characteristics is presented in Table 5-20. The simultaneous peak demand, the aggregate peak demand to be experienced by the transmission network as the individual DisCo maximum demand will not be coincidental, is on average 2% less than the non-simultaneous peak demand across the scenarios.

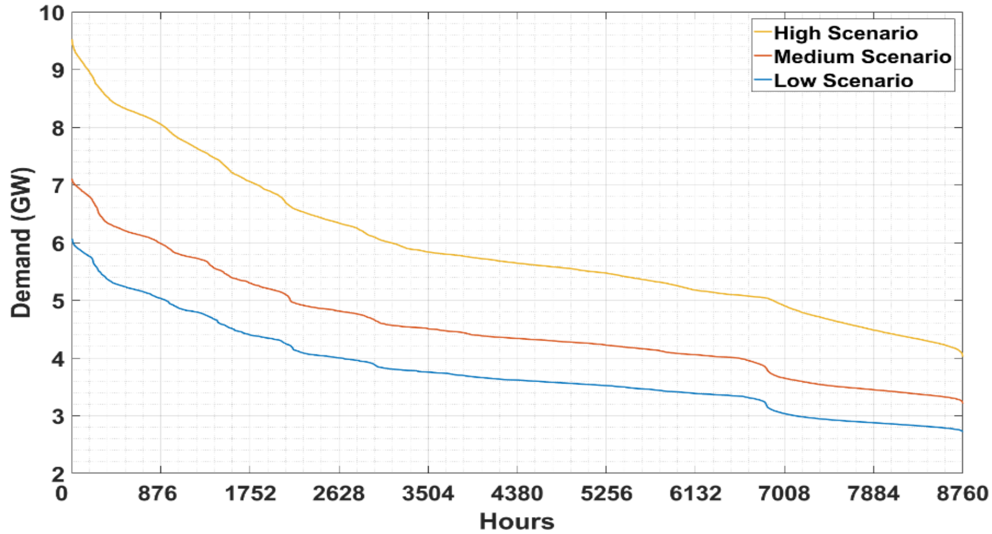


Figure 5-42: Total System Load Duration Curve

Table 5-20: Scenario System Energy Characteristics

Parameter	Unit	Low	Medium	High
Load Factor	%	60.5	61	62
Energy	TWh	30.6	37.1	49.5
Simultaneous Peak Demand	MW	5,489	6,534	8,991

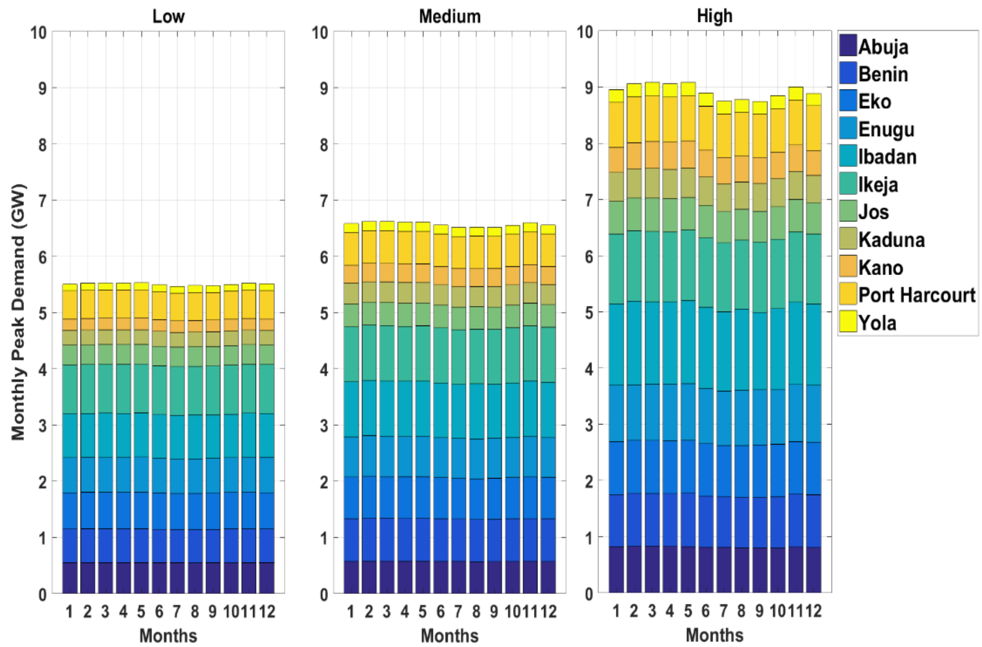
The scenario load factors compare well to the calculated value of 62% for Nigeria (Power Holding Company of Nigeria, 2009). There is no significant change in the load factor as household characteristics remain the same, appliance ownership increase is not accompanied with any change to the appliance ratings and efficiencies, and the load patterns for the non-domestic sector are static across the three scenarios.

With no recent transmission system reports from Nigeria to use for comparison, the system load factor is compared to values from other global transmission networks in Table 5-21. The load factor obtained from the load curve generated from the model compares well to the range of values obtained from those networks and under constant power supply conditions, the above load duration curves are considered representative of the national electricity demand pattern in Nigeria.

Table 5-21: Global Load Factors

Countries	Load Factor (%)	Source
Australia	55	(Independent Market Operator, 2014)
South Africa	61	(ESKOM, 2017)
UK	67	(Department for Business, Energy & Industrial Strategy, 2017)
US	53	(Hostick, et al., 2012)
Thailand	56	(Thailand Ministry of Energy, 2015)

Figure 5-43 shows the monthly system peak demand pattern. The changes in monthly peak demand which are more visible in the medium and high scenarios are influenced solely by the residential demand. Future work is needed to measure the influence of weather on non-domestic electricity demand in Nigeria to better capture the overall impact of weather on electricity demand.



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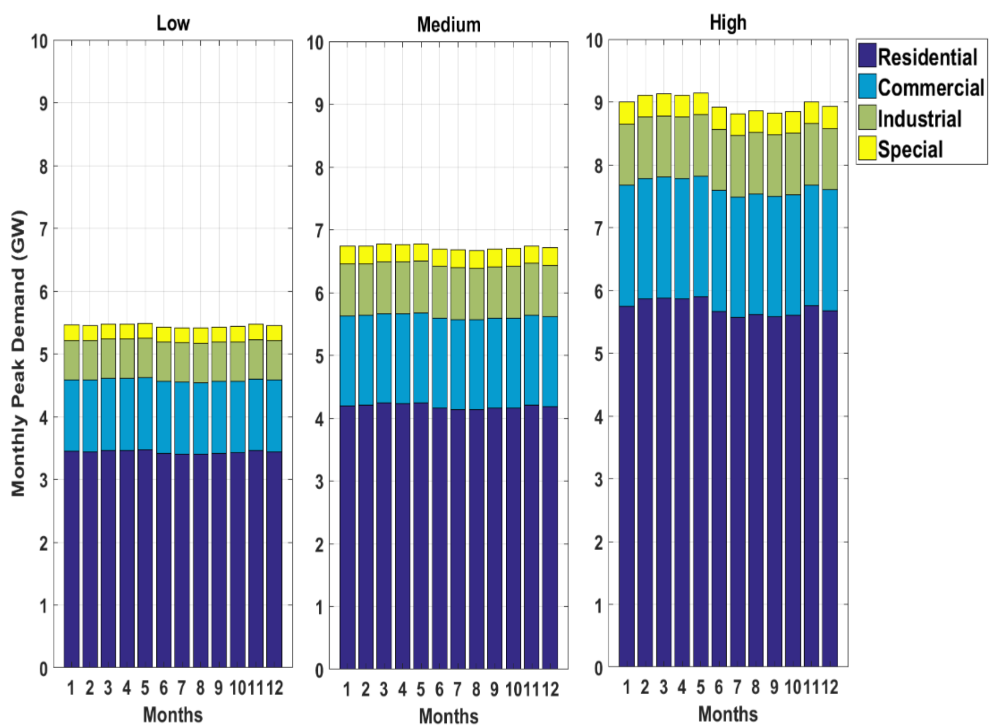

(b)

Figure 5-43: National Monthly Peak Demand
(a) Distribution Companies (b) Sectors

5.6 Summary

This chapter used a simple forecasting technique in conjunction with the residential demand model developed in Chapter 4 to estimate peak demand and generate demand curves for Nigeria. Reanalysis weather data used as input for the model has been analysed against measured weather data for Nigeria and discussed. Employing socioeconomic and geospatial reanalysis weather information for each state in the country as input data, residential demand curves were generated for each distribution network. The national system demand was constructed by aggregating the generated residential demand data with non-domestic demand forecasts from another study. The results from the model have been compared to other peak demand studies done for Nigeria. The next chapter will employ the demand data generated from this model and apply it to a representative Nigerian transmission network to assess the implications of supplying demand.

Chapter 6
Integration of Renewable Generation

The value of the time series national demand data generated from the demand model to power system analysis and planning for the Nigerian network will be demonstrated in this chapter. This chapter will analyse the impact of demand on generation technology type, reliability, operation costs and regulatory input for the Nigerian electricity market. A reliability assessment of the generation adequacy, capacity value assessment of renewable energy and a generation production cost benefit analysis of the integration of renewable energy into the Nigerian grid is presented in the following sections.

6.1 Renewable energy generation in Nigeria

As Nigeria aims to improve network reliability and increase its power supply, the generation technology options being considered are currently centred on fossil fuel and renewable energy generation (ICREEE, 2016). As at 2015, the total capacity of generation licenses issued by NERC was 31.5GW covering total existing, ongoing and proposed projects (NERC, 2015). Of this capacity, fossil fuel generation accounts for 81%, while renewable energy generation accounts for 19%. New hydro projects account for 5GW; wind projects, 0.1GW and solar projects 0.2GW. More recently, with the support of the U.S government through the Power Africa initiative, 14 solar projects with a combined capacity of 1.1GW have also received licenses from NERC and power purchase agreements from NBET (USAID, 2018). This growth in the adoption of renewable energy is also further supported by the government's policy on climate change, evidenced by its issuance of a green bond, the first of its kind in Africa (Bloomberg, 2017).

The assessment of renewable energy in solving Nigeria's energy deficit has been covered in literature. Oyedepo (2012), evaluates the impact of renewable energy in Nigeria's energy portfolio and recommends policy changes and the encouragement of renewable energy particularly for agricultural processes. Ohijeagbon and Ajayi (2015) assess the profitability of embedded solar generation across 40 locations in Nigeria. Olatomiwa (2015) proposes an optimal energy mix for rural customers in 6 different locations in Nigeria by analysing different energy supply configurations, with the objectives being met by the solar, wind, diesel and battery hybrid combination. Mentis, et al., (2015) use a geographic information system (GIS) approach for expansion planning in Nigeria exploring the inclusion of generation from solar, mini hydro schemes, wind and conventional generation on the current grid to achieve annual energy access targets for 33 million households. In that study, demand forecasting is based on domestic energy consumption of 170kWh/capita and 350kWh/capita, for rural and urban areas respectively, with a grid expansion cost of $15.4 billion to achieve 100% electrification. Ohiare (2015) and Bertheau et al., (2016) have also performed similar studies for Nigeria. Bertheau et al., (2016) perform their analysis based on domestic energy consumption of 840kWh/year and a household peak demand of 350W for an off-grid population of 15.6 million people and suggest a requirement for installation of 1.8GW of solar mini-grids and 0.1GW for solar-home systems. Ohaire (2015) proposes a least cost rural electrification plan that guarantees 100% electricity access, at a cost of $34.5 billion for 28.5 million people by 2030.

While these studies aim to show the improvement of the energy supply situation with the integration of renewable energy sources, the impact of their future integration on the system reliability is yet to be analysed. Time series demand and climatic data are some of the limitations that have limited such studies in sub Saharan African countries with similar renewable energy integration plans (Edwards, et al., 2017). In mature electricity networks, probabilistic generation adequacy and reliability studies are performed to measure the risk of inadequate generation capacity to meet demand during peak demand hours. These studies require technical generation station data as well as time series demand data to assess the influence of variables such as weather on both generation and demand. The temporal characteristics of individual sectorial demand on peak demand is also captured to effectively assess the relationship between generation and demand. The temporal variability of power supply from renewable energy sources adds another dimension to the reliability analysis for mature networks integrated with renewable energy.

In power systems planning, in order to evaluate the contribution of renewable generation technologies to the supply balance and reliability of a system, the estimation of the capacity value is usually performed. Capacity value can be defined as the amount of power capacity displaced by a candidate energy source while maintaining the original system reliability. This capacity valuation is based on a reliability indicator, defined as the probability of generation being inadequate to meet demand in a given period, and referred to as the loss of load probability (LOLP). This metric is a generally adopted index used in mature electricity networks for generation adequacy measurements and capacity valuation (IEEE, 2007). Capacity valuation methods are grouped into two categories, reliability based and approximation techniques (Madaeni, et al., 2013). Reliability based methods include the equivalent firm power, equivalent conventional power and the effective load carrying capability (ELCC), which is the more widely used method of reliability-based techniques. The ELCC method has been used to evaluate the capacity value of photovoltaic (PV) solar in the US (Munoz & Mills, 2015), (Madaeni, et al., 2012); PV in the UK (Dent, et al., 2016); as well as wind in the UK (Harrison, et al., 2015). Approximation methods which are valued for their lower computational burden compared to reliability-based techniques, include Garver's approximation method, ELCC approximation for multistate generators, Z method and the capacity factor-based approximation, which is most accurate of the approximation techniques as observed by Madaeni et al., (2013) in a PV capacity valuation method comparison for 14 U.S cities.

Based on the planned addition of renewable energy into the Nigerian energy portfolio, this study performs a system generation adequacy and reliability assessment for renewable energy integration.

While the capital investment costs associated with renewable energy expansion in Nigeria have been discussed in literature, an operational cost benefit analysis of renewables to the existing Nigerian grid is yet to be assessed. This research also assesses the cost benefit of grid expansion with renewables in Nigeria, with the minimisation of total energy production costs as the objective function. It uses a representative model of the Nigerian transmission network subject to unit commitment and transmission line constraints to perform an annual operating cost evaluation adapted to a simulated algorithm developed in the AIMMS optimisation environment (Robertson, 2018).

While onshore wind and solar PV projects have been earmarked for integration into the system grid, potential wind energy generation based on reported wind speeds can only be realised in the northern parts of the country, unlike solar generation which does not face similar locational constraints (Ojosu & Salawu, 1990) (Adekoya & Adewale, 1992) (Ohunakin, et al., 2011). Without available timelines for the completion of the renewable projects across Nigeria, this study will employ a long-term deterministic approach to evaluate the ELCC and cost benefit of renewables using historical weather data and electricity demand generated from the national demand model.

6.2 Model Data

6.2.1 Demand

Hourly demand time series data generated from the national demand model is used in this analysis. The high scenario demand with a peak demand of 9.1GW discussed in Chapter 5 is used to evaluate the capacity value and cost analysis of the renewable energy sources.

6.2.2 Conventional Generation

A capacity outage probability table is developed using a recursive model in the estimation of the LOLE, and for each unit provides both the individual probability that it will be out of service, and the cumulative probability of a finding a unit on outage equal or greater than that unit's amount (Billiinton & Allan, 1996). This analysis is based on the reliability index of the units as each unit in the system has an availability rate and can be in one of two states i.e., 'on' or 'off', depending on its availability. As discussed in Chapter 2, the availability is determined by the forced outage hours, scheduled maintenance hours and total supply hours. Probability *P(x)* is the cumulative probability of capacity outage of a system with x capacity after unit y is added to the system (Billiinton & Allan, 1996):

$$P(x) = p_y\, P'(x-y) + q_y P'(x) \tag{6.49}$$

where P' is the cumulative probabilities of capacity outage before unit y is added to the system, p_y is the unit y availability rate and q_y is the unit y unavailability rate. Across the system, for any given configuration of capacities, Equation (6.49) can be modified to

$$P(x) = \sum_{i=1}^{n} p_i P'(x - c_i) \quad (6.50)$$

where n is the number of unit states, c_i is the capacity outage of state i for the unit being added and p_i is the probability of occurrence of unit state i. Generation unit data for the Nigerian grid is obtained from (Nigeria Electricity System Operator, 2018). Table 6-1 shows the total installed capacity for the study period, but non-operational turbines have been excluded from the data. Without available data for all generation units, the availability rates used for this analysis is obtained from a study by Oyedepo et al., (2015) who performed a technical reliability assessment of 11 gas turbines across 3 generation stations in Nigeria for an analysis period of 5 years (2005-2010). Generator station data is presented in Appendix C.

The mean availability (%) of the units ranged between 65.2 and 87.8, with a standard deviation (%) between 0.81 and 23.5. For unavailable generation stations, the average availability rate from that study of 78% has been used. The resource interdependence and seasonal dependence nature of hydro generation means the historical (2013-2016) capacity factor values of each hydro station has been used instead.

Table 6-1: Grid connected conventional generation capacity

Power station type	No. units	Capacity (GW)
CCGT	13	1,936
OCGT	89	5,451
Steam	12	1,848
Hydro	18	1,900
	132	11,135

Availability metrics are defined by the numbers of 9's past the decimal point, with best rating of 0.99999 or 5-9's as defined by IEEE (2007). The survey values show low reliability values compared to the 0.9 of the UK for OCGT and CCGT (National Grid, 2010).

Figure 6-1 shows the probability distribution of generation availability obtained using Equation (6.50) with an expected value of 8.1GW and a standard deviation of 0.5GW. The current available generation capacity is 7.7 GW (Nigeria Electricity System Operator, 2018), which shows a good estimation of current availability has been made based on the assumptions used.

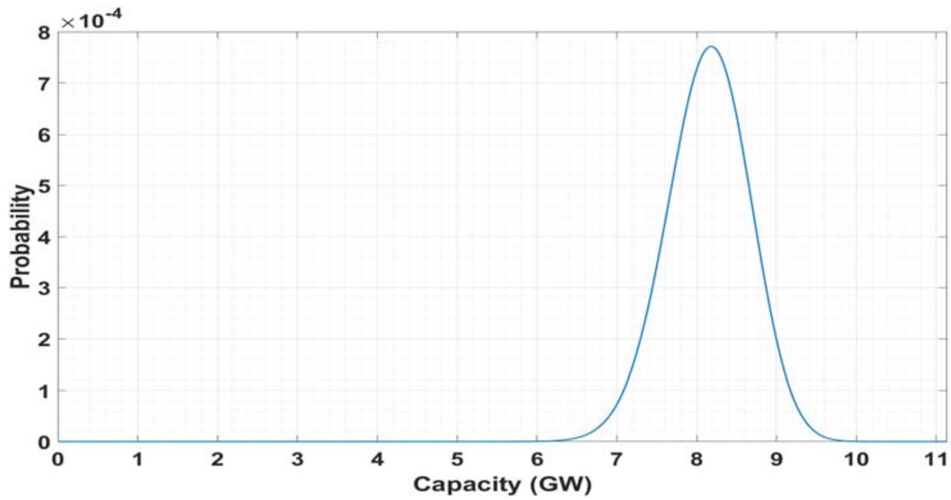

Figure 6-1: Probability distribution of generation availability

6.2.3 Solar Data

NASA MERRA-2 global horizontal irradiance and extra-terrestrial radiant flux data is the data source for this model. In order to capture the spatial effect of solar irradiance across the country, each of the eleven DisCo regions is allocated a solar farm with equal power production capacity. For simplicity, hourly irradiance data has been obtained for the state with the highest peak demand in each DisCo location. 100MW PV farms are installed in each location and the capacity at each farm is increased in steps of 50MW until each farm reaches a target capacity of 500MW, bringing the total installed capacity to 5.5GW. With MERRA-2 data having a 50km by 50km resolution, each selected location is deemed sufficient to represent the irradiance effects for the assumed installed solar farm capacity, as solar farms with similar capacities to the target capacity have much smaller area (KSPDCL, 2016). In this study, solar energy is modelled as being produced from commercial farms only and does not include rooftop PVs.

The weather model discussed in Chapter 4 was updated to include a solar PV component that simulates the production of electrical energy from a solar farm. Power production from a solar is calculated as follows (Tian, et al., 2012):

$$PV_t = W_{panel} \times \left(\frac{E_t}{E_{Ref}}\right) \times P_{rel} \times \mu_{inverter} \qquad (6.51)$$

$$P_{rel} = 1 + \left(t_{factor} \left(T_{cell,t} - T_{STC}\right)\right) \qquad (6.52)$$

$$T_{cell,t} = T_{amb,t} + E_t \times ptc \qquad (6.53)$$

where PV_t is hourly power production (W) at time t, W_{panel} represents the rating and number of panels installed, E_t is the total irradiance on tilted panel surface (W/m^2), E_{Ref} is solar irradiance at standard test condition (1kW/m^2), P_{rel} is the relative performance of the panel, $\mu_{inverter}$ is the inverter efficiency, t_{factor} is the temperature coefficient of the panel (°C) , $T_{cell,t}$ is the hourly panel temperature (°C), T_{STC} is the temperature at standard conditions (°C), $T_{amb,t}$ is the hourly ambient temperature (°C), and ptc is the temperature dependent panel efficiency (°C/Wm^2). Panel assumptions are mono crystalline 250W rated panels, with an area of 1.552 m^2 and a normal operating cell temperature of 46.5°C. An inverter efficiency of 0.96 has been used. The panels are modelled as fixed ground installations, facing the true south (zero orientation) and with a panel tilt equal to the latitude of each location (Li & Lam, 2007) (Jamil, et al., 2016).

Nigeria receives an abundance of annual sunshine and irradiance, with average daily sunshine hours of 6.3hours/day and average daily irradiance ranging between 3.7kWh/m^2 day in the coastal regions to 7.0kWh/m^2 day in the northern arid regions (Ojosu, 1990) (Fadare, 2009).

The solar PV model performance is shown in Figure 6-2 with the mean daily irradiance results. Eko and Ikeja DisCos both serve Lagos and are both represented by Eko. The mean daily irradiance results range from as low as 3.58 kWh/m^2 day in Port Harcourt, to as high as 7.14 kWh/m^2 day in Kano. The lowest irradiance values are observed in Port Harcourt and Lagos, both coastal regions, with the highest values observed in Kano, Jos and Yola, which are located in the northern region of the country. Inter-annual variation in solar irradiance is observed across the locations with increases noticed in the 2015 mean values compared to the 2014 values in 6 of the 10 locations.

There is a decline in 2016 mean irradiance values compared to the 2015 values in 8 of 10 locations. Ibadan is the only exception with minimal inter-annual variance observed in the daily irradiance values. The mean annual daily irradiance is 4.9 kWh/m^2 day, 5.1 kWh/m^2 day and 4.8 kWh/m^2 day for 2014, 2015 and 2016 respectively.

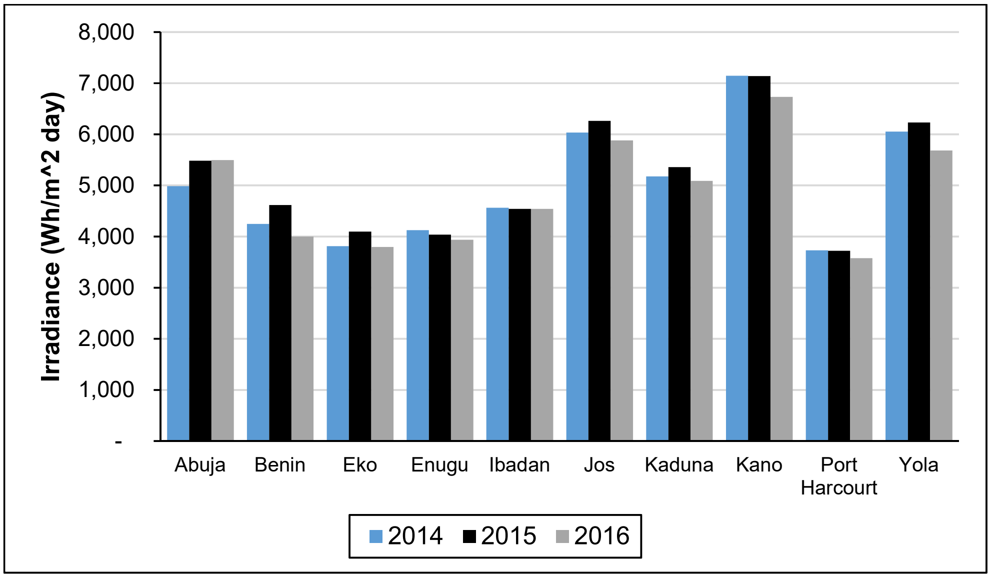

Figure 6-2: Mean daily irradiance

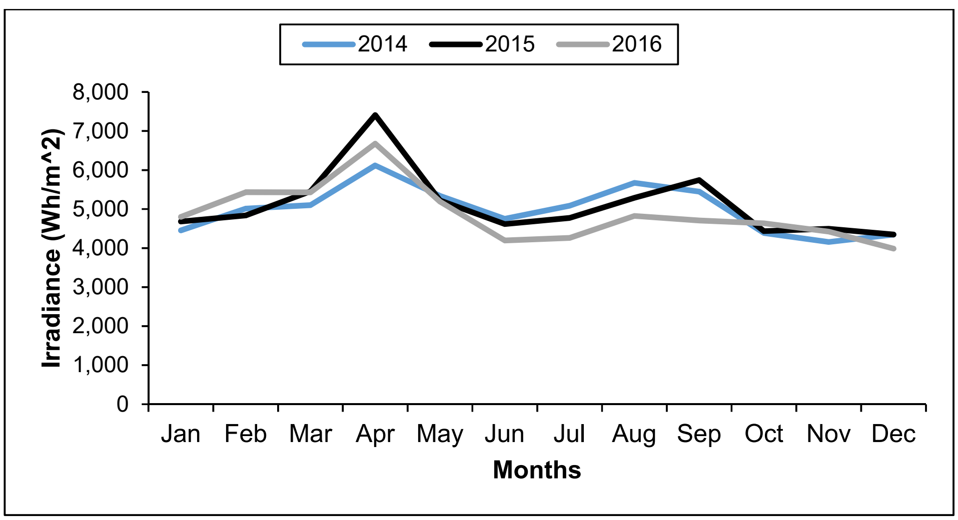

Figure 6-3: Aggregate annual irradiance variation

The mean monthly irradiance profiles are shown in Figure 6-3, with peak values observed in April (dry season in the north), and a flatter shape for other months of the year. This effect is due to the increased cloud cover during the rainy season months, followed by sustained hazy conditions during the dry season months (harmattan). The inter-annual variations can also be seen from the monthly differences in irradiance value across the study years.

Capacity value estimations are sensitive to the time series demand data used for the analysis due to the importance of the temporal coincidence between demand and renewable energy generation. Although variable in its intra-day intensity, solar energy can only be produced during the daylight hours, as opposed to a variable resource like wind which is available throughout the day. Seasonal variations affect the sunshine hours due to changes in weather variables such as the humidity, temperature, wind speed and cloud cover. In temperate regions, the longest sunshine hours occur in the summer months, and the shortest sunshine hours occur during the winter. This seasonal change also affects the demand pattern with peak demand occurring in the winter months as the need for heating increases, and the lowest demand typically occurring during the summer months (National Grid, 2010). As such it might be useful to carry out capacity value assessments of renewable energy generation using the hourly demand for peak periods, as it provides a useful measure of the contribution of the energy technology to the system reliability during the stress case scenario provided by the peak demand hours.

In tropical climates, it is expected that demand will increase during the dry season due to increase in cooling demand as shown in Chapter 5, if AC ownership is high. In Nigeria, a tropical country with 2 seasons, the average sunshine hours vary from about 7.2 hours in the dry season to 4.20 hours in rainy season (Ojosu, 1990). The variability is greater in the south of the country which experiences longer rainy season days compared to the north, with minimal variance observed between the seasons in some northern locations. Hence for simplicity in the assessment the solar capacity value, this analysis estimates capacity value for annual demand data rather than the seasonal demand data as the seasonal changes in sunlight hours varies across the country.

6.2.4 Wind Data

Wind data analysis

2014-2016 NASA MERRA-2 hourly eastward and northward wind speed data is the data source for this model. The longitude, latitude and elevation of the 5 locations selected for the wind capacity installations are shown in Table 6-2. MERRA-2 hourly wind data is available at a 50m height resolution and corrected to an 80m resolution, which is the wind speed obtained at the assumed wind turbine hub height. This is achieved using the log law (Harrison, et al., 2008):

$$U(z) = U(z_r)\left(\frac{\ln\left(\frac{z}{z_0}\right)}{\ln\left(\frac{z_r}{z_0}\right)}\right) \tag{6.54}$$

where $U(z)$ and $U(z_r)$ are the wind speeds (ms^{-1}) at the required z and reference z_r heights respectively (m), and z_0 is the terrain dependent roughness length. An open grassland is assumed for the turbine installations; z_0 is 0.03m.

Table 6-2: Location of Wind Turbines

		Coordinate		
Location	DisCo	Lat. (°N)	Long. (°E)	Elevation (m)
Jos	Jos	9.87	4.97	1285
Kano	Kano	12.05	8.53	472
Katsina	Kano	12.8	7.41	517
Nguru	Yola	12.70	10.27	342
Sokoto	Kaduna	12.28	4.13	350

The mean monthly wind speeds at 80m hub height for the five locations are shown in Figure 6-4. The annual wind speed pattern across the locations can be readily seen, with maximum values observed between December and January, and minimum values observed between August and October. All locations follow this trend, however the peak noticed in April is more significant in Nguru compared to the other areas.

Nguru also experiences an earlier pick up in mean wind speed at the start of the dry season in September compared to the other locations. From the results, it appears that the wind speeds at the various locations have a stronger correlation with seasonal patterns than the elevation of each site. Stronger wind speeds are observed during the dry season, with lower speeds observed during the rainy season. The dry season is characterised by the southward migration of the Tropical Continental Air Mass (TCA) from northern to southern Nigeria between December and March. The TCA, also known as harmattan, which originates from the Sahara Desert, is a dusty and hazy wind, with low humidity. Maximum wind speeds, which occur in the dry season, range between 6.87 m/s and 8.39 m/s, with the highest values obtained in Katsina.

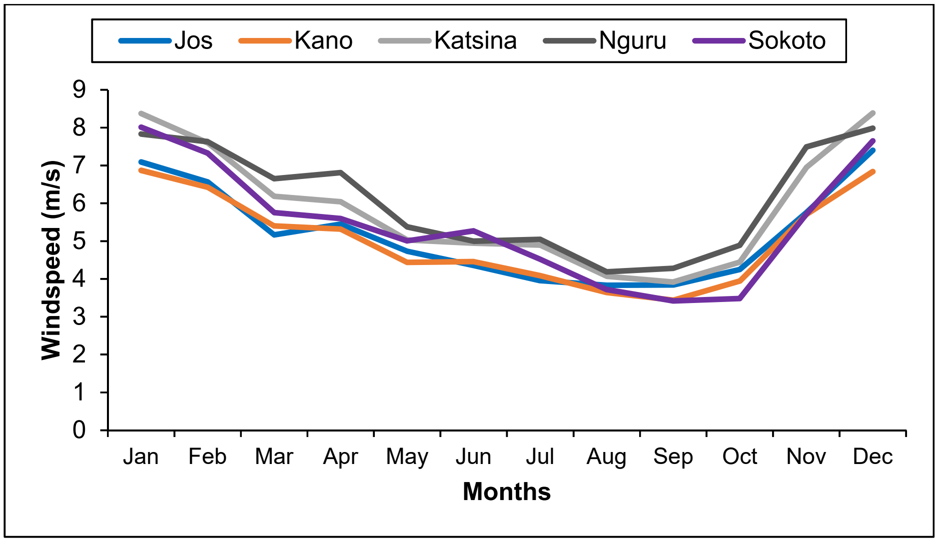

Figure 6-4: Mean Monthly Wind Speed (m/s)

The mean seasonal wind speeds are also shown in Table 6-3. Figure 6-5 shows the annual hourly wind speed profiles for the five locations. The results from this current research are compared to two previous wind generation surveys performed for Nigeria. Ojosu and Salawu (1990) performed their survey for 22 cities in Nigeria, all of which are covered in the current study, while Ohunakin, et al., (2011) performed their study for 7 cities, 3 of which are covered in the current study. Each study is indicated by the year of publication in Table 6-3. The mean dry season speeds range between 6.09 m/s and 7.40 m/s, with the highest dry season wind speeds observed in Katsina. The mean rainy season speeds range between 4.00 m/s and 4.80 m/s. For the selected locations, the annual mean wind speeds range between 5.05 m/s and 6.10 m/s, with the lowest speeds observed in Kano.

While the regions with higher elevation, Jos and Katsina, have relatively higher wind speeds during the rainy season, overall the impact of elevation on wind speed appears to be minimal as the location with the lowest elevation has the highest annual mean speed. The annual patterns observed from the model, agree with the seasonal patterns but differ in values when compared to the findings by Ohunakin, et al., (2011). The 2011 was performed using historical daily data which was recorded at just two respective times of the day.

The results are more consistent with the results from Ojosu and Salawu (1990), who performed their study using historical daily 3-hourly recorded data. To enable comparison, the 1990 study which used 10m height wind speeds was corrected to the 80m equivalent. The intraday variation in wind speeds requires multiple daily measurements, as the daily patterns reveal higher early morning wind speeds, which steadily decline to minimum values in the late afternoon, before increasing gradually into the night.

Table 6-3: Seasonal mean wind speeds

	Current Study			1990	2011
Location	Rainy	Dry	Annual	Annual	Annual
Jos	4.16	6.24	5.20	5.28	N/A
Kano	4.00	6.09	5.05	4.19	7.77
Katsina	4.55	7.25	5.90	N/A	7.45
Nguru	4.80	7.40	6.10	5.07	N/A
Sokoto	4.23	6.67	5.45	5.33	7.61

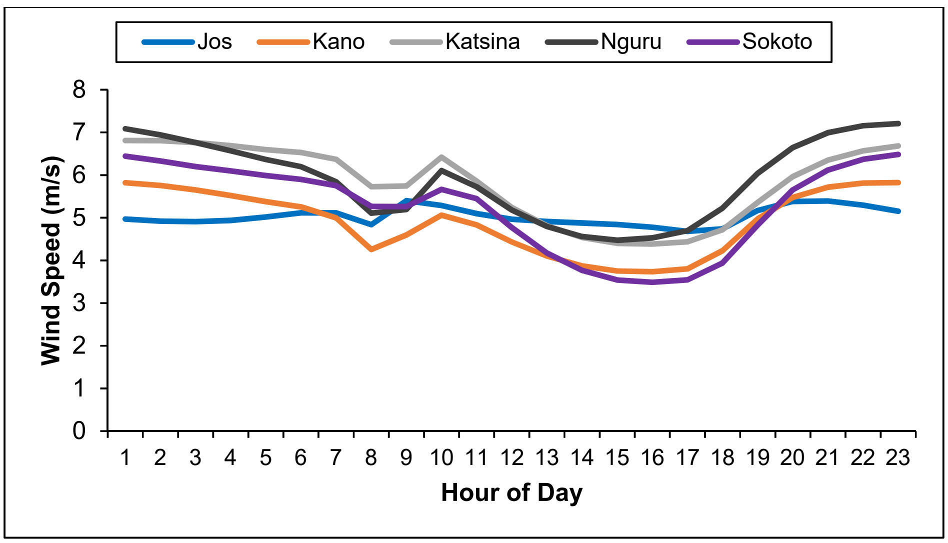

Figure 6-5: Mean annual hourly wind speed profiles

The inter-annual variations in the aggregate annual mean speeds are also shown in Figure 6-6 (these are averaged across the five locations). The annual profiles emulate those shown of the locational monthly results in Figure 6-4, with a notable spike occurring between March and April in the 2015 data. While similar annual patterns are observed for the years studied, differences in the monthly values for each year studied shows that inter-annual variations are captured in this analysis. The mean aggregate annual wind speed for 2014, 2015 and 2016 are 5.43 m/s, 5.74 m/s and 5.44 m/s respectively.

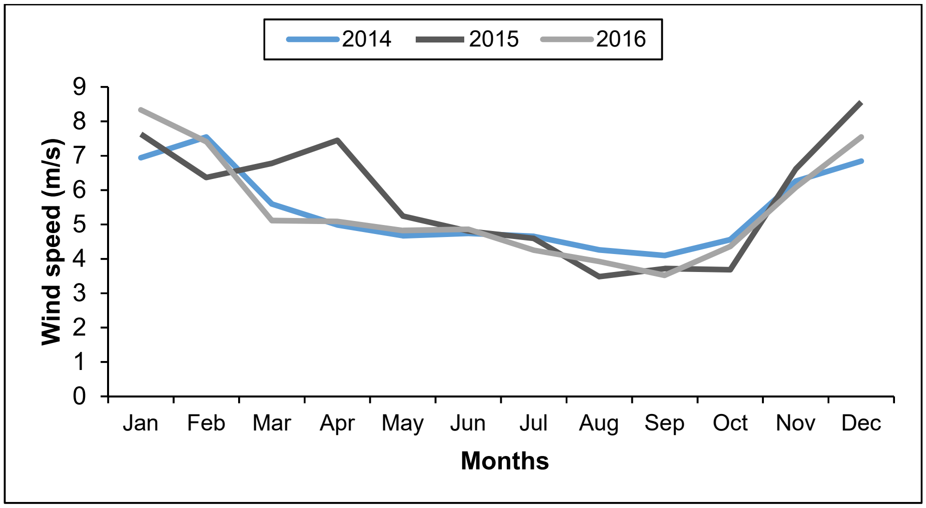

Figure 6-6: Aggregate annual variation in wind speed

The use of climatic reanalysis data in weather simulations requires bias evaluations, as this research has shown the potential seasonal bias in the MERRA-2 data for temperature. Monthly variation comparisons with Ojosu and Salawu (1990), reveal seasonal wind speed underestimation particularly during the rainy season for Kano and Katsina. Staffel and Pfenninger (2016) reveal spatial wind capacity factor bias ranging between 5-50% across Europe using MERRA reanalysis data; bias correction was then performed using measured wind speed data from the studied locations. Unavailable measured data means bias correction cannot be currently be applied, however due to similarities in annual mean speeds between the current study and Ojosu and Salawu (1990), the data is regarded as suitable to capture the variation in wind production. The seasonal bias effects will be analysed as part of the future work of this research, with measured wind speed data.

<u>Wind Power Production</u>

A total wind generation target capacity of 0.8GW is spread across 3 DisCo regions, with installations in 5 locations. Wind generator locations are selected based on current generation licenses, an ongoing project in Katsina, Nigeria (Okoronkwo, et al., 2016) and previous wind generation surveys for Nigeria (Ojosu & Salawu, 1990) (Adekoya & Adewale, 1992). Each location is assumed to have 20MW of wind and this is incremented in 20MW units up to 160 MW, i.e. 100 MW aggregate steps.

Available wind power is obtained from the kinetic energy of moving air as it crosses the swept area of the wind energy conversion system. Available wind power P_{WD} (W) can be expressed in terms of cross-sectional area A of the conversion system (m), the wind speed U (ms^{-1}), and the air density ρ (kgm^{-3}) using (Harrison, et al., 2008):

$$P_{WD} = \frac{1}{2}\,\rho A U^3 \tag{6.55}$$

The significance of the cubic relationship between wind speed and power production is that a change in wind speed results in an even greater change in power production. The power production is also dependent on the efficiency of the wind energy conversion systems (WECS). For this study, the chosen turbine is a 3 MW Vestas V90, which has a 90m rotor diameter and a hub height of 80m. This wind turbine is operational between its cut-in and cut-off speeds of 3 and 25 ms^{-1} respectively, with its maximum (rated) power production obtained at speeds greater than its rated speed of 15 ms^{-1} (Vestas Wind Systems A/S., 2004).

6.3 Generation Analysis

6.3.1 Conventional Generation Capacity Availability

The baseline LOLE was calculated for each of the 3 demand scenarios (low, medium and high) with the 11.1GW conventional generation capacity. In both the low and medium demand scenario, LOLE is less than 1 day in 10 years, while that of the high demand scenario is 439hours/year. The increasing magnitude of peak demand across the scenarios sees a corresponding increase in system risk and unavailability probabilities.

A typical LOLE standard for large interconnected networks in the USA is one day in ten years, for UK it is 3hours/year, while that of European countries vary from one day in fifteen years, to one day in two and half years (IAEA, 1984). The prevalent load shedding and frequent system collapses experienced by the network is as a result of inadequate generation capacity due to maintenance and unit unavailability (NESI, 2015). With the current power supply shortages being experienced in Nigeria, improvements in individual unit availability rates will be beneficial to the electricity market.

Based on the high level of system unreliability obtained using the current units' availability, a reference $LOLE_{BASE}$ of 10hours/year is used for this analysis by adjusting the availability of thermal generation stations to a value of 0.85.

6.3.2 Solar Generation

Aggregate daily solar generation for the target installed solar capacity of 5.5GW is shown in Figure 6-7. This data represents the power generation for one week in March, a selected dry season month, for each year of the study period. The intra-annual and inter-annual variance in energy resource are seen in the daily changes in aggregate power production. The annual difference in resource distribution translates to an aggregate energy production of 10.2 TWh, 10.3 TWh and 10.1 TWh, for 2014, 2015 and 2016 respectively for the target capacity. This yields an aggregate annual capacity factor of 21.4%, 21.6% and 21.2% for the same years respectively.

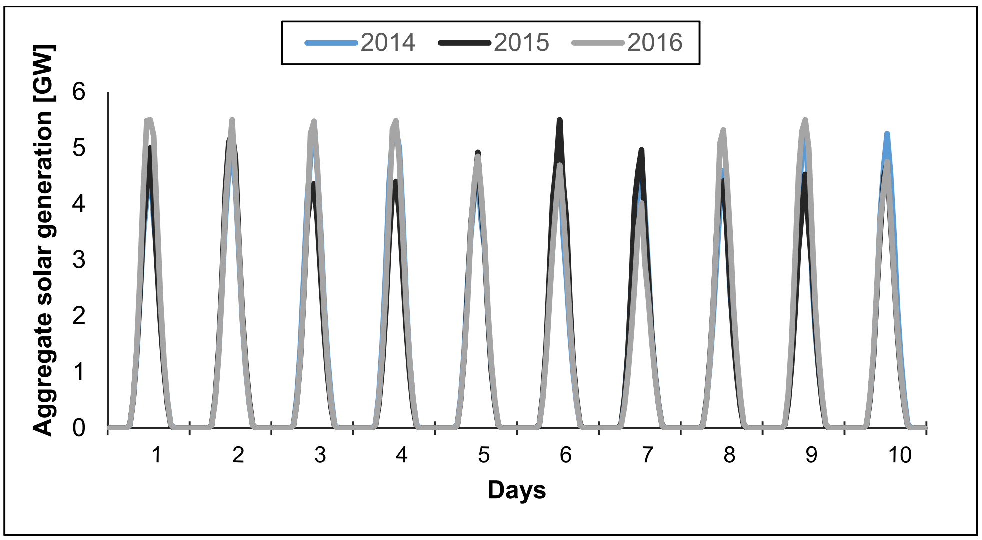

Figure 6-7: Aggregate solar generation for 5.5GW capacity – 10 days in March in each year

The generation contribution from each installed location is shown in Figure 6-8. The annual capacity factor across the locations follows a similar annual trend as the irradiance data, with values ranging from as low as 18.0% in Port Harcourt, to as high as 26.1% in Kano. The regions in the north have an average annual capacity factor of 23.5%, compared to the aggregate average of 21.4%.

Based on the irradiance data evidence and modelled solar generation output, it appears the northern region of the country has a stronger potential for solar energy generation compared to the southern regions.

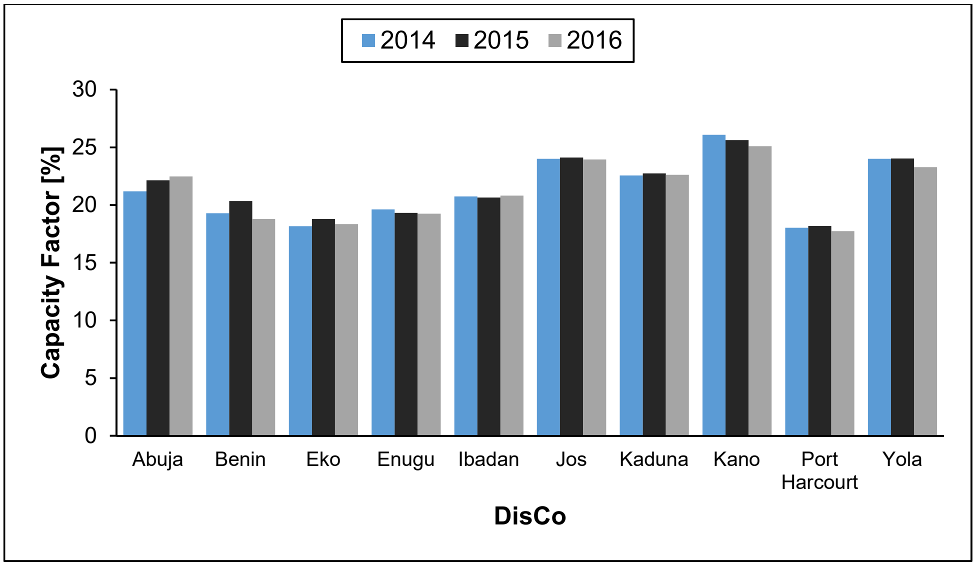

Figure 6-8: Annual solar capacity factor for each location

6.3.3 Wind Generation

The aggregate wind capacity factor for 2016 is shown in Figure 6-9. The pattern of distribution across the year shows stronger production in the early and late months of the year, which make up the dry season period. Wind production during the rainy season, the midyear months, is lower in comparison to the dry season. The low level of production will also be impacted by the seasonal bias discussed in section 6.2.4.

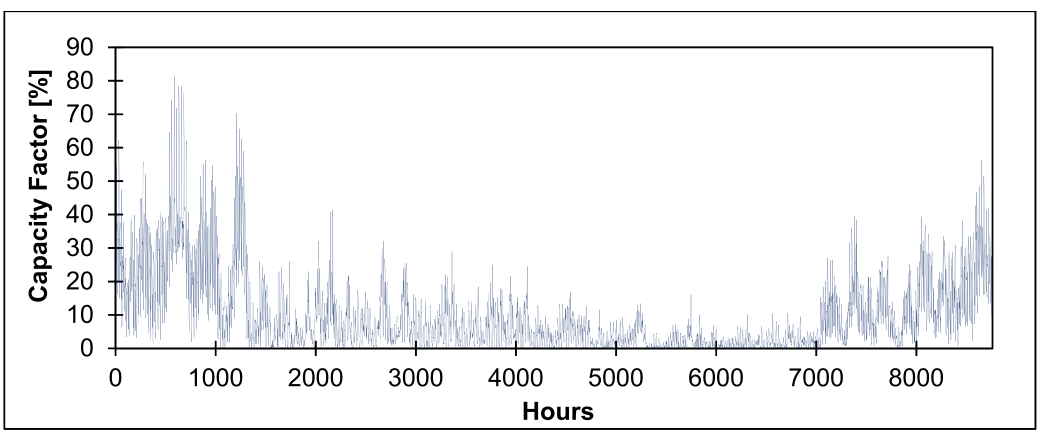

Figure 6-9: Aggregate wind generation capacity factor

The annual mean capacity factor per location is presented in Table 6-4. The capacity factors obtained follow the locational wind speed trend, with Nguru and Sokoto producing the highest amount of wind energy over this period. The hourly differences in the power production profiles can be seen, as can the variance in daily generation.

Table 6-4: Annual Mean Capacity Factor

	Capacity Factor (%)		
Location	2014	2015	2016
Jos	7.3	10.5	8.1
Kano	6.5	8.1	6.8
Katsina	11.9	14.5	12.6
Nguru	12.3	15.0	13.1
Sokoto	9.2	11.9	10.0
Aggregate	9.5	12.0	10.2

The annual mean capacity factor per location varies between 6.5% and 15%, with the highest values obtained in Katsina and Nguru. Across the five locations, the aggregate annual mean capacity factor varies between 9.5% and 12%.

Similarly, the aggregate daily wind generation for the target installed wind capacity of 800 MW, for ten days in March, is shown in Figure 6-10. Figure 6-11 shows the annual duration of renewable energy production. The annual difference in resource distribution translates to an aggregate energy production of 660 GWh, 841 GWh and 708 GWh, for 2014, 2015 and 2016 respectively.

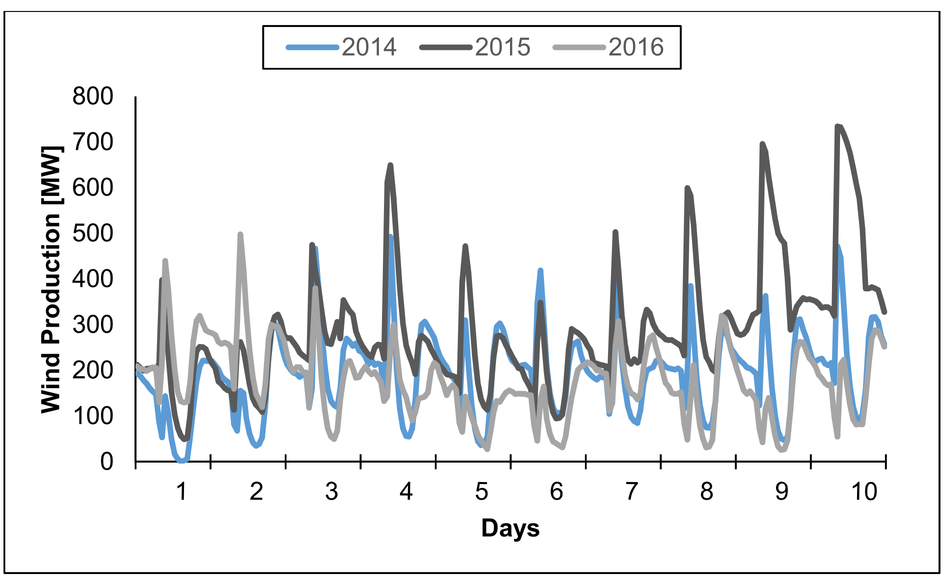

Figure 6-10: Aggregate wind generation for 800MW capacity – 10 days in March

While the frequency of wind generation is higher than that of solar generation, with an annual power production frequency of 94% compared to the 55% of solar generation, the seasonal dampening effect on wind speeds reduces the magnitude of its total generation resulting in an underutilization of capacity for most of the year. The total period of wind generation greater than half the installed capacity is 65 hours of the year (1%), compared to the 18% for solar generation. This tends to suggest that the V90 turbine is not adequately tuned to the Nigerian wind regime. Future work will evaluate turbine types that guarantee optimal production for Nigeria.

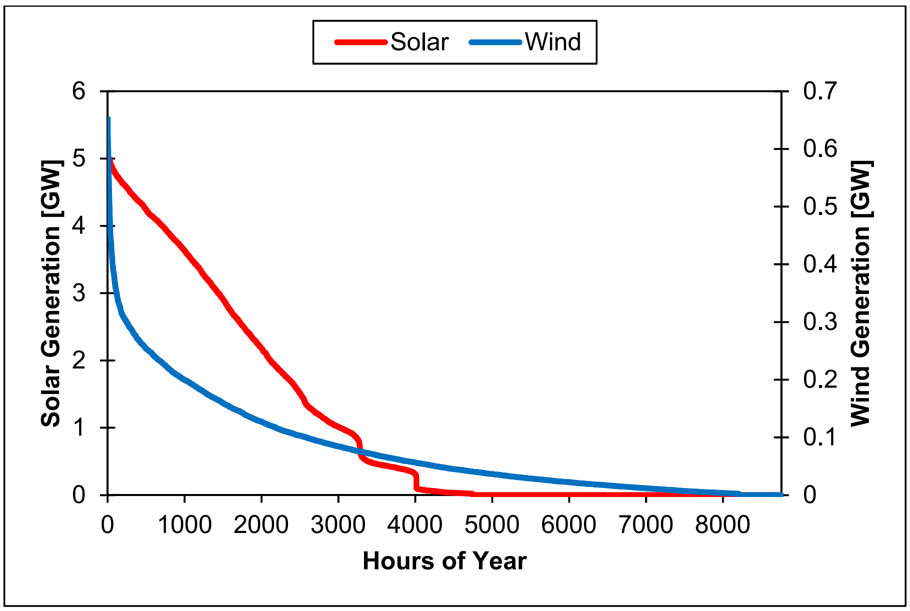

Figure 6-11: Annual duration of solar and wind generation

6.4 Reliability Assessment

6.4.1 Capacity Value Estimation

Power system reliability indices comprise of probabilistic and deterministic indices (IAEA, 1984). Probabilistic indices reflect system uncertainty, while deterministic indices describe the reliability status of existing system conditions. The LOLP is a reliability index used to evaluate the probability in period t (hour) that some amount of demand will be unserved by the available generation capacity in the system. It can be expressed using (Harrison, et al., 2015):

$$LOLP = p(X_t < D_t) \tag{6.56}$$

where X_t is the available generation capacity (MW) and D_t is the system demand (MW). The summation of the LOLP over the entire analysis period T gives the loss of load expectation (LOLE) which is expressed in time unit/year. It can be expressed as:

$$LOLE = \sum_{t}^{T} p(X_t < D_t) \qquad (6.57)$$

The ELCC is a probabilistic system reliability index used to evaluate the reliability contribution of a generation unit to a system. It can be defined as the maximum demand which can be added to a system after the addition of a new generator while maintaining the initial system reliability.

This is described using Figure 6-12 which shows the ELCC of generation unit addition. The reliability design criterion of the presented system is an LOLE of 0.1days/year, given by the horizontal line passing through line D-E. Point A represents the LOLE at acceptable initial condition of less than 0.1days/year before increased demand to the system moves the LOLE above point D to B (>1days/year), increasing the probability of system's inability to meet demand. The integration of an additional generation unit to the system shifts the curve to the right, and reduces the LOLP from point B to point C, which is equal to the original system reliability value at A. The difference between points D and E defines the contribution of the additional unit of generation to the system reliability and gives the ELCC.

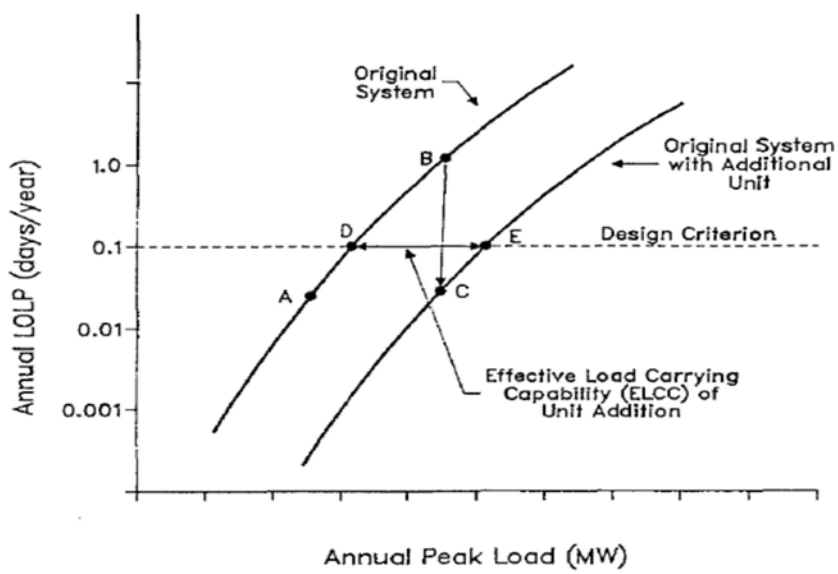

Figure 6-12: ELCC of generation unit addition (IAEA, 1984)

The ELCC is estimated using the following steps:

1. The LOLE is estimated using a reliability model of existing conventional generators on the system, and the hourly demand data to calculate the hourly LOLP and evaluate the $LOLE_{INITIAL}$ for the analysis period using Equation (6.57).
2. Hourly renewable generation output RE_t is deducted from the demand and step 1 is performed again to obtain $LOLE_{RE}$. $LOLE_{RE}$ will be lower than $LOLE_{INITIAL}$ as the demand evaluated in this stage is the 'net demand', indicating the addition of new production to the system.
3. In an iterative process, a quantity of demand d_{ELCC} is added to the entire demand time series and the $LOLE_{DEMAND}$ is evaluated in each iteration until the $LOLE_{INITIAL}$ is obtained.

$$LOLE_{DEMAND} = LOLE_{INITIAL} = \sum_t^T p(X_t < D_t + d_{ELCC} - RE_t) \tag{6.58}$$

The capacity value (%) of renewable generation to the system is then expressed as a ratio of d_{ELCC}: total renewable capacity.

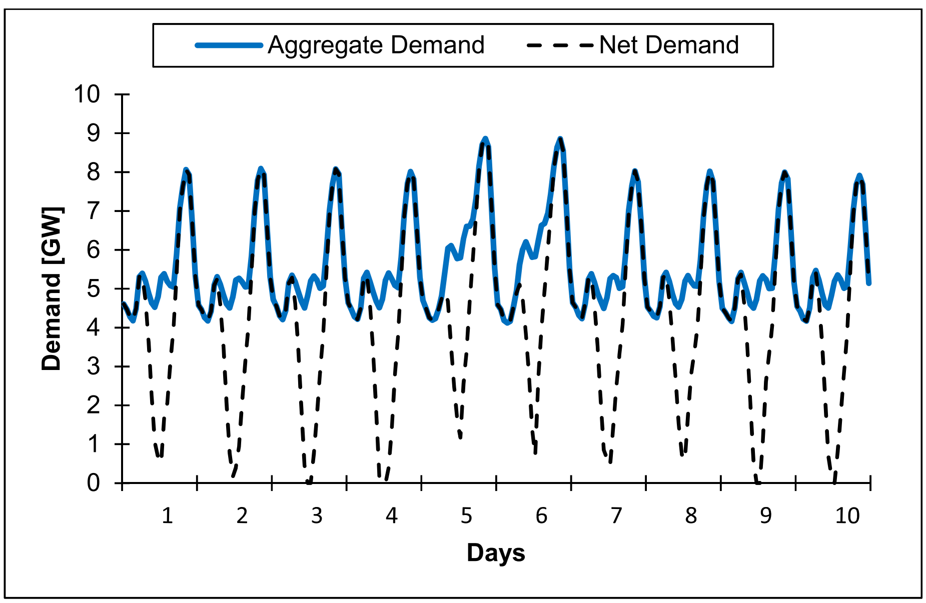

Figure 6-13: Daily aggregate and solar net demand

Figure 6-13 shows the daily aggregate demand and solar net demand. The peak solar output and demand mismatch is evident as the solar generation net demand, is only realised during the midday without any impact on peak demand which occurs at night.

The deduction of the generated solar power from the demand gives the net demand. It is to this net demand that recursive additions in demand (d_{ELCC}) are made to calculate the capacity value of solar generation that achieves the same level of reliability obtained from conventional generation.

With inter-annual variations observed in renewable energy resources, study periods of multiple years are recommended (Madaeni, et al., 2013). Harrison, et al., (2015) performed capacity value of wind analysis for the U.K using 10 years (2000-2010) of wind resource data, while NREL (2011) performed a capacity value analysis of wind integration for the eastern U.S using wind resource data for a three-year period (2004-2006). The current study performs the analysis over a three-year period (2014-2016). Hourly demand data is generated from the national demand model and used in the analysis. Current generation capacity is based on the total installed capacity at the end of 2016. For the solar PV capacity addition, a spatial approach is employed that sees an equal capacity of power plants built in each DisCo region (Figure 6-14).

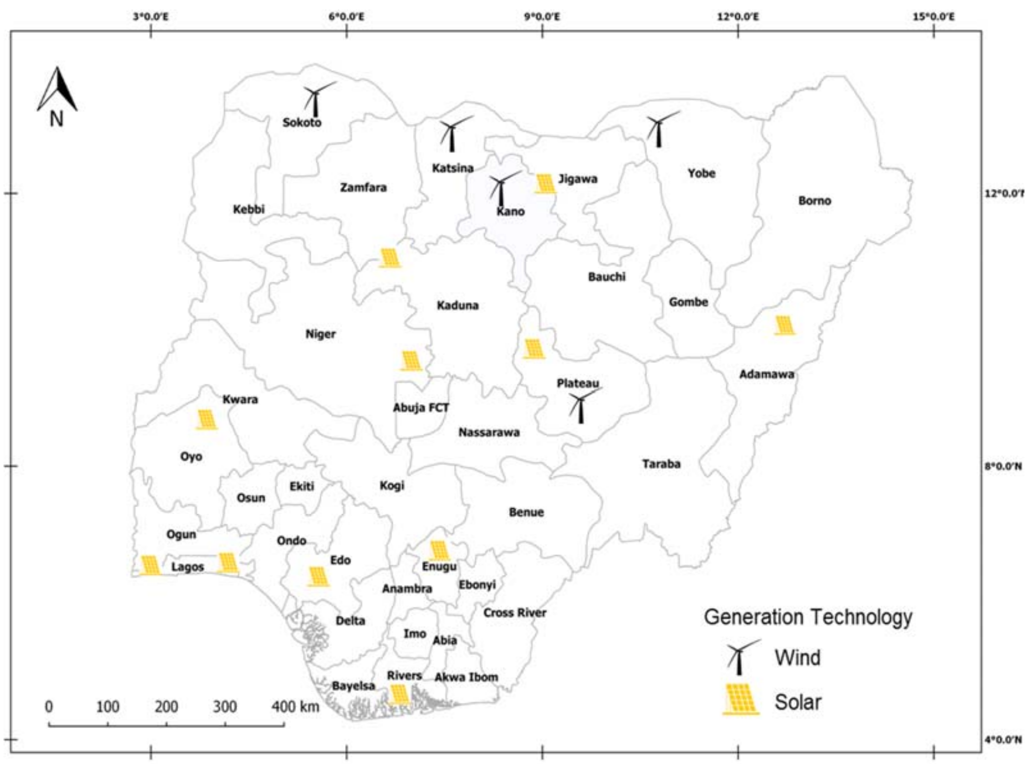

Figure 6-14: Capacity location of renewable generation

This approach is guided by the government's target solar capacity of 5GW by 2030, resulting in an assumed target capacity of 500MW for each DisCo. For the wind capacity addition, an equal capacity of 160MW is assumed to be built in each of the 5 selected locations. This analysis has been performed with MATLAB.

6.4.2 Demand and Solar Generation

The time series demand data for ten days in March is shown in Figure 6-15. National demand data for the high scenario corresponding to 2016 weather discussed in 6.2, and the aggregate solar energy production for 2016 is shown. The intraday as well as daily variations in the demand data can be seen, with a slight early morning peak and a more significant late evening peak demand. The late evening peak demand occurs between 8pm and 10pm, driven by the domestic demand. From the simulated national demand data, domestic energy contribution to the total energy consumption is 51%.

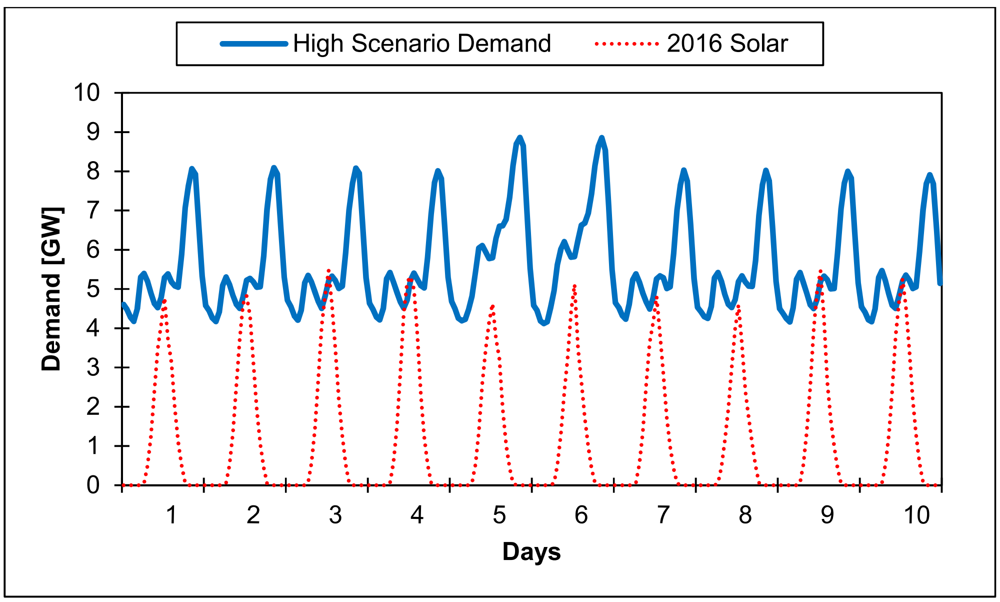

Figure 6-15: Demand and solar generation for 5.5GW capacity

Although daily variance is expected in the magnitude of solar generation output, its daily production window is constant for Nigeria as shown in Figure 6-16 which gives the aggregate mean daily irradiance for 2016, with aggregate daily peak production occurring between 11am and 2pm. The level of coincidence between the daily production period and the daily peak demand will affect the capacity value, as solar power production with a higher coincidence with demand will produce a higher capacity value and vice versa (Madaeni, et al., 2013).

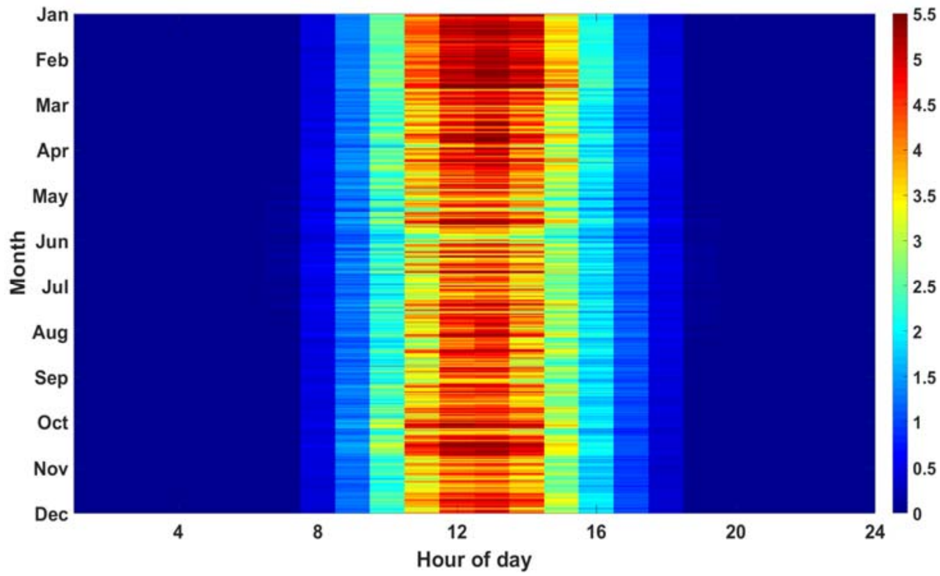

Figure 6-16: 2016 Hourly irradiance (kWh/m^2)

The hourly net demand from solar generation is shown in Figure 6-17. Between 11am and 2pm, solar generation reduces the aggregate demand significantly, however, the period with peak demand, between 8pm and 11pm, is not impacted by the solar generation output.

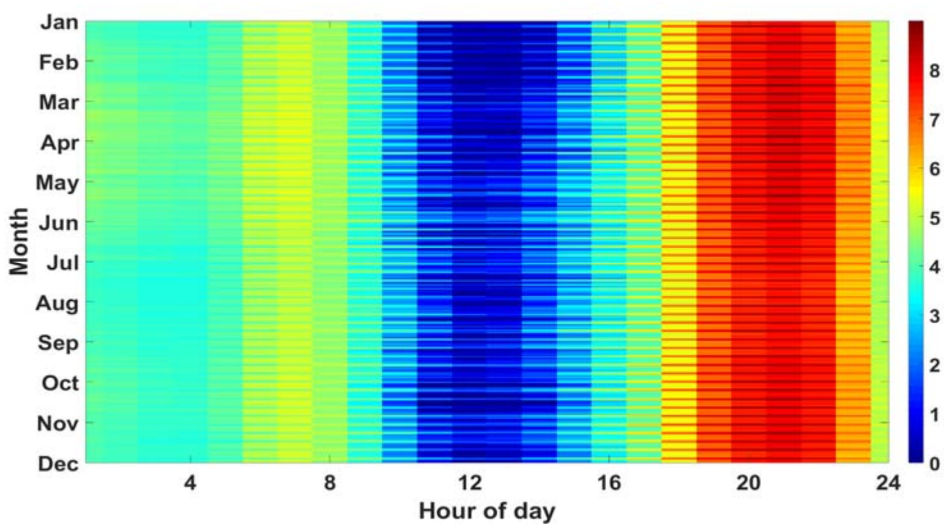

Figure 6-17: Hourly solar net demand (GW)

This mismatch seen between daily peak demand and daily peak energy production is thereby expected to constrain the impact of solar generation in reducing the risk of generation inadequacy during peak demand hours and system reliability. This mismatch is witnessed for the entire duration of the data analysed. While this study has not accounted for the potential direct impact of solar generation increasing midday domestic and non-domestic demand, the uncertainty of behavioural response to increased solar generation capacity will be challenging to quantify and has therefore not been included in this analysis. The impact of solar generation on total demand sees the midday demand reduced to negligible levels (coloured blue) but has no impact on the peak nightly demand period coloured red.

6.4.3 Demand and Wind Generation

The relationship between demand and wind generation is shown in Figure 6-18. The daily variation in wind power production can be seen, and unlike the solar output, its production is not constrained to a fixed daily time period. There is a high level of coincidence between wind production and daily peak demand as seen on days 3 and 4, and the wind power profile shows power production throughout the day. The level of coincidence between wind power output and peak demand is considerably higher than that of solar. However, the annual production of wind generation is less than the contribution from solar generation mainly due to the lower wind speeds obtained in during the rainy season.

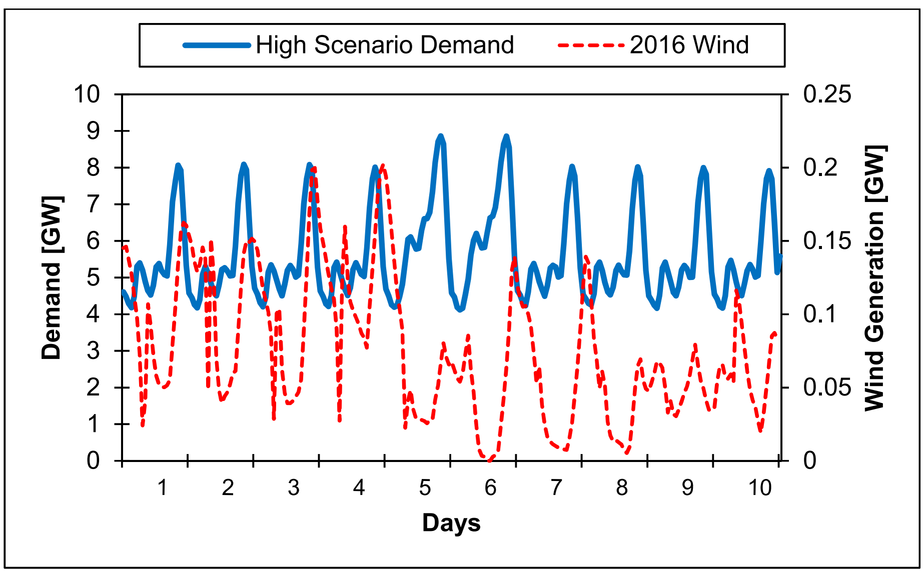

Figure 6-18: Demand and wind generation for 800MW capacity

Figure 6-19 shows the aggregate wind capacity factor for 2016. It can be seen that the power production from wind is high between the late evening and mornings, between 8pm and 12 noon, with peak production observed between 9am and 11am. However, this production is prominent only during the dry season months, with minimal production obtained during the rainy season.

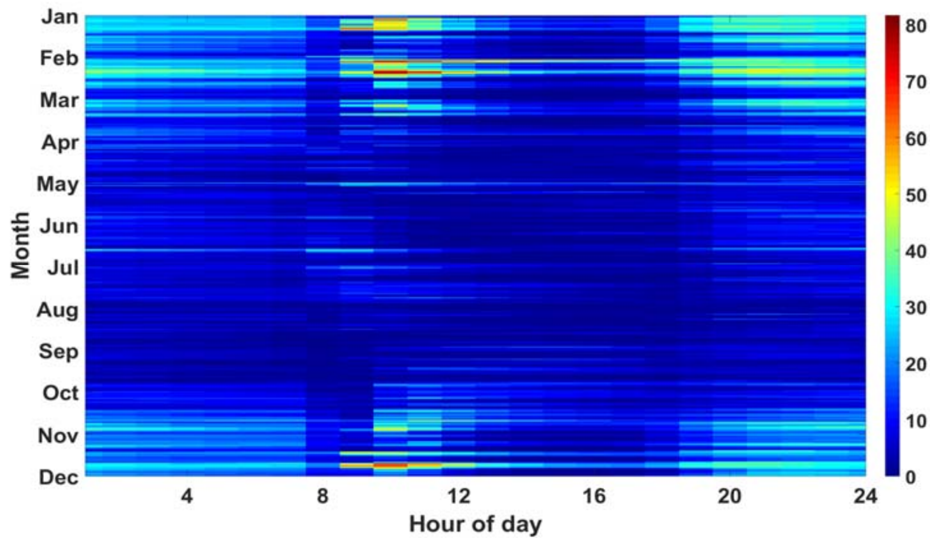

Figure 6-19: Aggregate capacity factor (%)

This seasonal effect constrains the impact of wind generation on the annual demand as shown in the net demand presented in Figure 6-20. The more constant output reduces the daily demand and with a noticeable effect on the daily peak demand between 8pm and 11pm. The net demand with wind generation during the daily peak demand period is considerably less than that of solar shown in Figure 6-17.

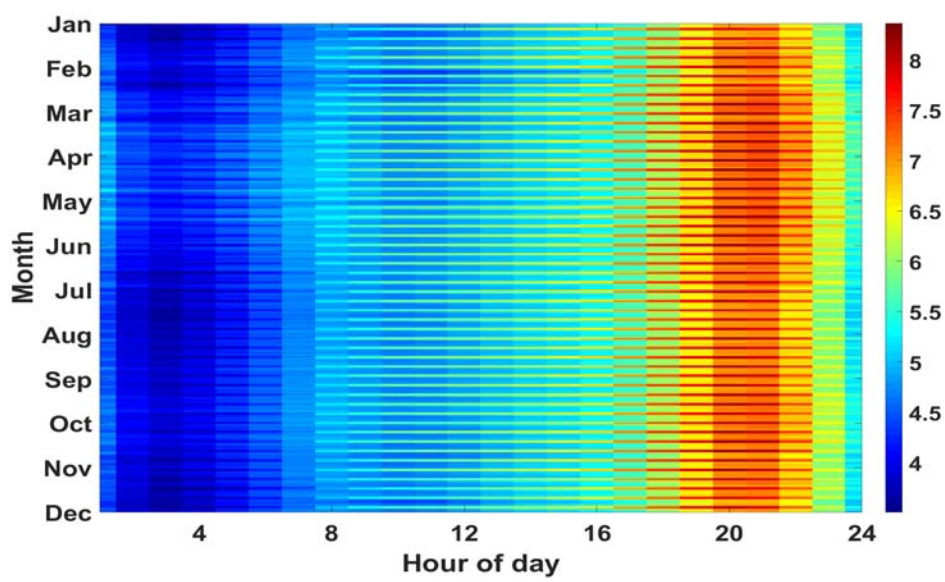

Figure 6-20: 2016 High demand scenario – wind net demand (GW)

With a higher level of coincidence between daily peak demand and wind production, it is expected that to some extent, wind generation should have more of an impact on reducing the risk of generation inadequacy. This impact will tend to be realised during the dry season, as the production during the rainy season is minimal.

6.4.4 Solar Capacity Value

Aggregate Demand

The capacity value analysis is performed using the high scenario demand data, due to the negligible solar capacity impact on the low and medium scenario demand. The capacity value is estimated for the aggregate installed capacity at each DisCo. The capacity at each solar farm is increased in steps of 50MW, which gives aggregate increments of 550MW across the distribution companies.

Figure 6-21 which shows the solar capacity value for the aggregate total demand. The peak daily peak demand and solar production mismatch is evidenced with the minimal range of less than 1% obtained for each increase in the aggregate installed capacity. The downward sloping curve of the high demand scenario results from a diminishing contribution to system reliability as the total installed solar capacity increasingly reduces the solar generation net demand as the target installed solar capacity is achieved. A reduction in demand reduces the risk of generation capacity inadequacy and improves the system reliability.

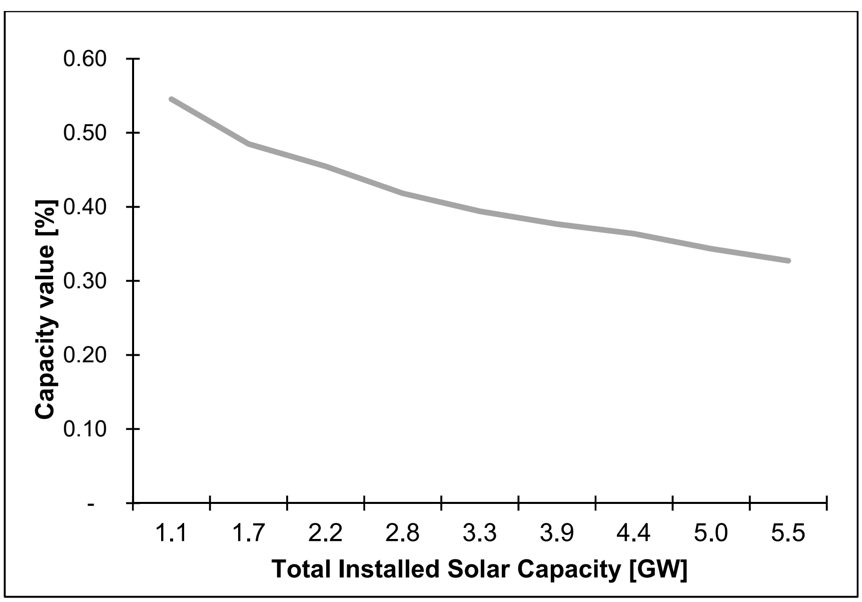

Figure 6-21: Solar capacity value for aggregate total demand

Conventional generation capacity reduction

The initial analysis was performed with an assumption of zero transmission constraints which is not the case in the Nigerian network, as transmission network related constraints are 6.5% of the total installed conventional generation capacity (NESI, 2015). The impact of transmission constraints on the solar capacity value is further evaluated for two transmission constraint levels of 5% and 10%, by reducing the conventional generation capacity by these percentages. The reduction of conventional generation capacity yields an expected value and standard deviation of capacity availability of 7.7GW and 0.47GW with 5% reduction, and 7.3GW and 0.49GW with 10% reduction respectively.

Figure 6-22 shows the results after reducing the conventional generation capacity. The solar capacity value to the system rises with a reduction in conventional generation capacity as shown by the higher values of the 10% system capacity reduction compared to the 5% system capacity reduction and initial system capacity, over the long-term solar capacity growth.

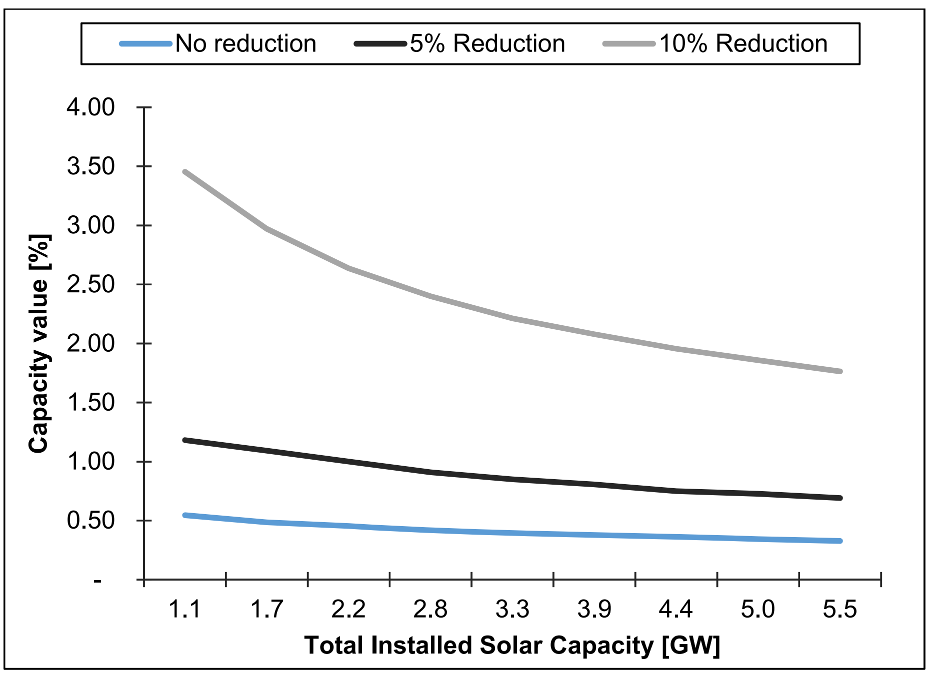

Figure 6-22: Solar capacity value for reduced conventional generation capacity

The reduction in generation capacity raises the system risk due to a higher probability of generation unavailability with each reduction in capacity, as the initial LOLE

($LOLE_{INITIAL}$) before capacity reduction rises from 10 hours/year to 54 hours/year and 196 hours/year in the 5% and 10% reduction levels, respectively. While the temporal mismatch between peak demand and solar generation still persists, the reduction in conventional generation capacity raises the risk of the generation capacity unavailability for all hours of the analysis period, thereby increasing the reliability contribution of solar generation during the daily irradiance hours. The integration of solar generation into the grid then results in a substantially lower $LOLE_{PV}$ calculated using step (2) of section 6.4.1, as the demand is reduced by the solar generation output thereby decreasing the system risk levels. The higher the risk levels in the system, the greater the reliability benefit provided by additional generational capacity, which in this case is provided from solar generation. The disparity between $LOLE_{INITIAL}$ and $LOLE_{PV}$ determines the magnitude of demand (d_{ELCC}) that can be added to the system. The higher the difference, the riskier the system and the more solar capacity is required to offset the risk; the lower the difference, the more reliable the system is, which reduces the need for additional solar capacity. In this case, the 10% reduction level generates the highest system risk and results in the largest difference between $LOLE_{INITIAL}$ and $LOLE_{PV}$ for each MW of solar capacity installed compared to the 5% reduction level and the initial system level.

Aggregate non-domestic demand

Due to the mismatch observed between peak solar generation and demand, a further analysis was performed to assess the solar capacity value for the aggregate non-domestic sector demand i.e., total aggregate demand minus domestic demand. In more industrialised nations in the West (Madaeni, et al., 2013), peak demand occurs in the middle of the day, with a higher coincidence with solar production yielding a higher range of capacity values as compared to the earlier set of results shown in Figure 6-22. This analysis is important as it highlights the potential future reliability contribution of solar to the grid, as Nigeria's demand profile evolves with an increase in industrialisation.

This analysis uses the target capacity assumptions of 5.5GW for solar generation and aggregate capacity increments of 550MW. Figure 6-23 shows the aggregate and net non-domestic demand for a 10-day period in March. The weekly profile of the non-domestic demand shows higher weekday demand compared to weekends (Days 5 and

6). The daily profiles of the non-domestic demand show peak demand occurring at the middle of the day which increases the coincidence with solar power generation as shown by the demand 'hair-cuts' of the net demand effected during the peak demand hours.

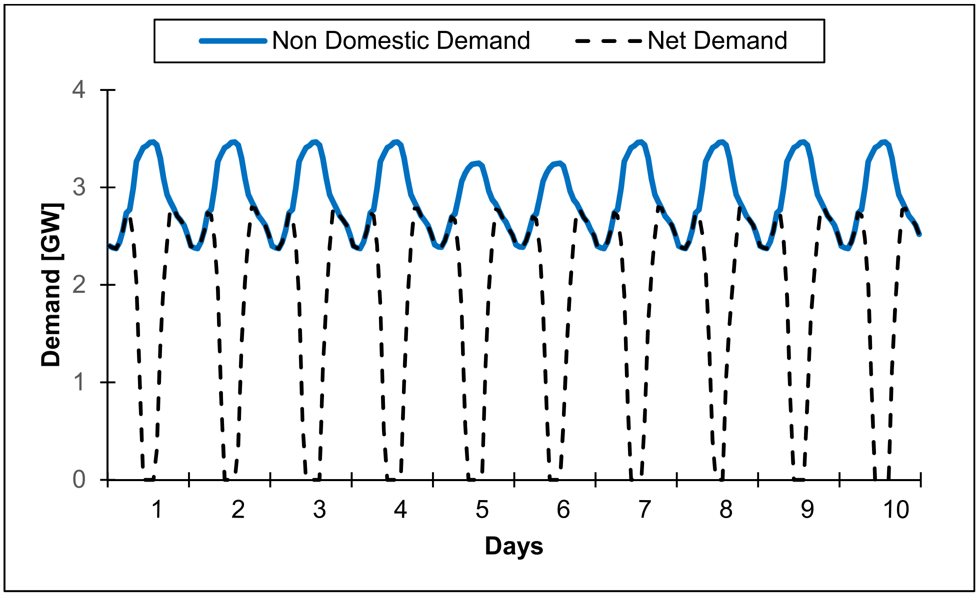

Figure 6-23: Daily aggregate and net solar non-domestic demand

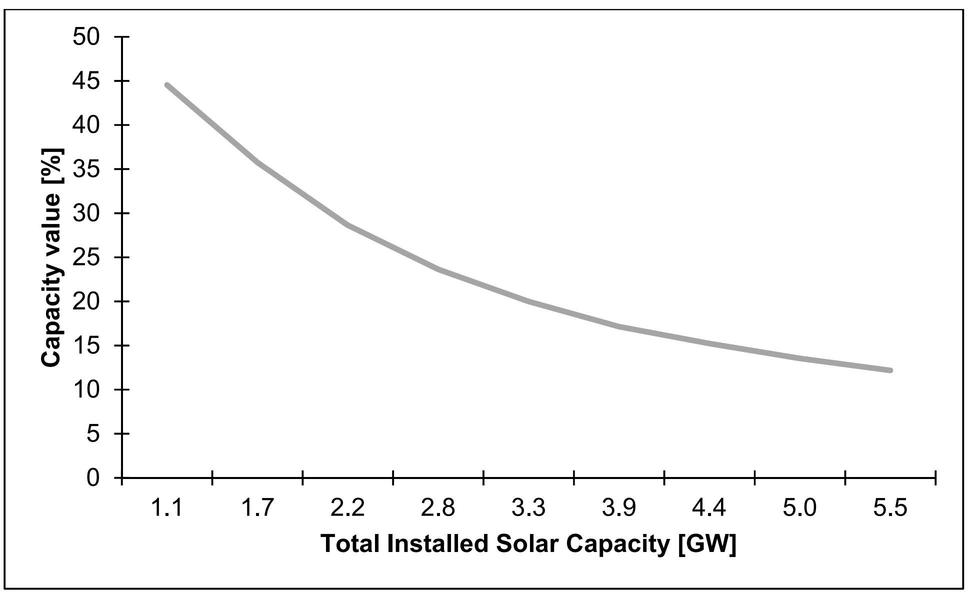

Figure 6-24: Solar capacity value for aggregate non-domestic demand

This translates to a higher range of capacity values for the aggregate non-domestic demand as shown in Figure 6-24. The impact of solar energy generation on non-domestic demand is more significant compared to the results obtained for the aggregate total demand driven by the temporal characteristics of both demand profiles. Solar capacity installations will have an immediate impact on non-domestic demand with a capacity values of 45% at the initial phase, with a gradual reduction to 12% by the target installed capacity of 5.5GW.

6.4.5 Wind Capacity Value

The magnitude of installed wind capacity, as well as the capacity factor results in a minimal change in the profile of the net demand compared to the aggregate demand (Figure 6-19). However, the high coincidence of wind production with daily peak demand reduces the risk of generation inadequacy and results in a higher range of capacity values in comparison to solar generation. Figure 6-26 shows the wind capacity values to the grid. The sensitivity of the wind capacity values to the reduction in conventional generation was also performed. The integration of 100MW of wind capacity sees an initial capacity value vary between 13.3-14.7% for the conventional generation percentage reductions of zero, five and ten, respectively. A decrease in capacity value accompanies increases in installed wind capacity, which sees the reduction varying between 12.7-13% for the 800MW target capacity for the conventional generation capacity reductions. The significant difference in the magnitude of demand and aggregate installed wind capacity results in a flatter slope of capacity values compared to those shown for solar. The range of capacity values obtained are also similar in magnitude to the aggregate mean capacity factor for wind. The results show that wind generation has a higher capacity value for the Nigerian network when compared to solar generation without battery storage.

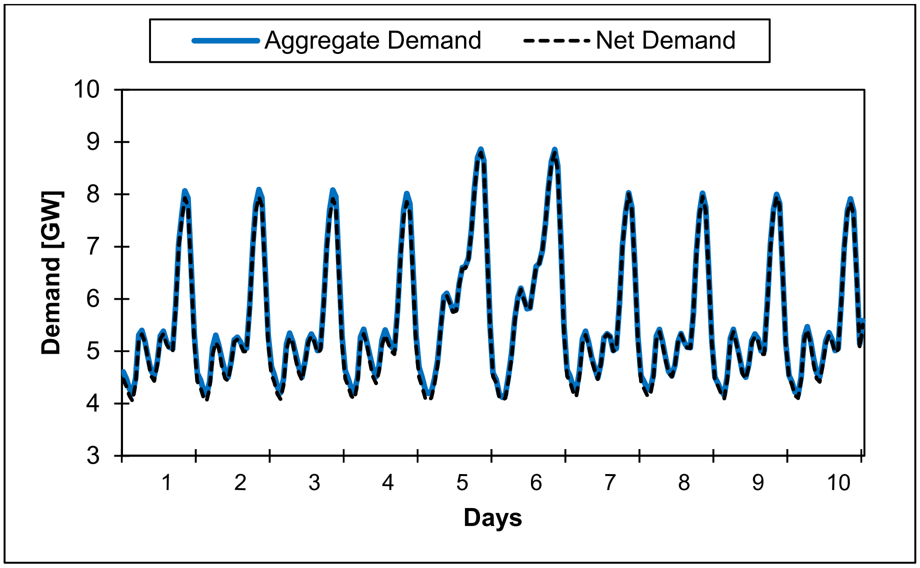

Figure 6-25: Daily aggregate and wind net demand

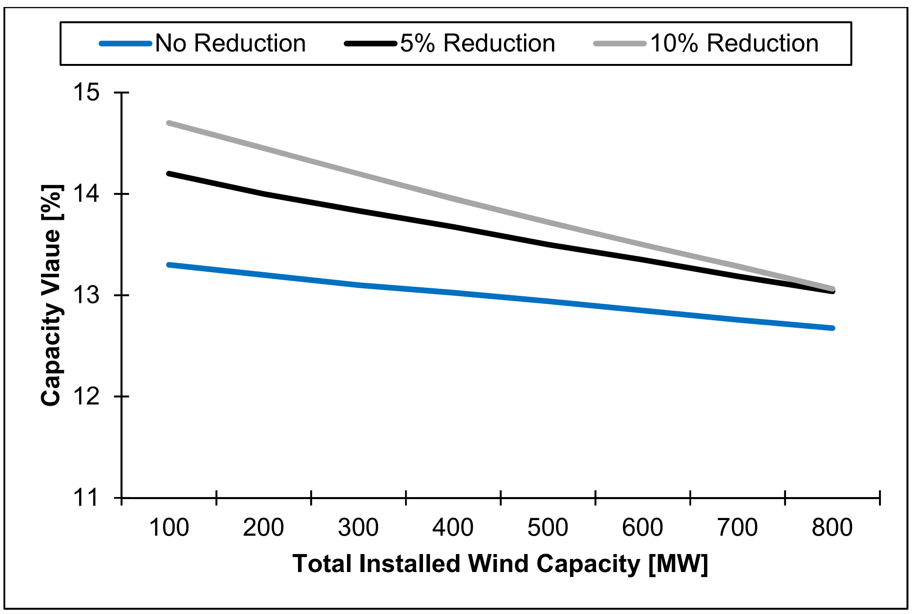

Figure 6-26: Wind capacity value for aggregate total demand

6.5 Energy Supply

6.5.1 Unit Commitment Analysis

The cost benefit of the integration of renewable energy on the network is analysed using a test network representative of the Nigerian grid. A deterministic approach is employed here, with reliability considerations implemented on the network with the addition of a reserve margin requirement, and the production of energy based on the availability rates of generating units. A 59-bus network of the 330kV transmission level is used for the analysis; details of the buses are included in Appendix C. The evaluation of the cost of electricity production is done with the national demand data, using the actual operating cost data for conventional generators on the Nigerian network as contained in the NERC (2015) MYTO II wholesale generation prices, and EIA (2016) operating cost estimates for the renewable generation. Ramping constraints, shutdown and start-up costs are not evaluated as part of this analysis. While the relaxing of certain unit operational constraints could potentially introduce a cost bias in the planning model, a generation expansion cost analysis performed by Jin, et al., (2014) showed a cost difference of 0.02% between a unit commitment model and an economic dispatch model with reduced constraints. Moreover, the cost data required as part of the formulation could not be obtained from the generation companies due to its nature of its sensitivity.

The unit commitment model evaluates the operating cost using a moving horizon criterion, sequentially providing an optimal cost solution for each day in the year. The total daily generating cost is evaluated on an hourly basis determined by the operating costs of each generator, the availability of conventional generators and the hourly resource availability of both solar and wind. The generation dispatch also accounts for the possible hourly curtailment of both renewable resources when deemed optimal to do so. Curtailment events take place to reduce renewable energy supply in periods with low demand, or when transmission congestion on the network is observed (Bird, et al., 2014). The unit commitment model for the Nigerian system of B buses with G generators and an aggregate installed renewable generation capacity RE over period T (hrs) is implemented as:

$$\min \sum_{g \in G} FC_g b_g + (MC_g + cb_p)\, p_{g,t} + \ C_{uns} uns_{b,t} + \ C_{sr} usr_t \\ + \ C_{curt} rc_t \tag{6.59}$$

Subject to the following constraints:

1. Power supply balance and reserve

$$\sum_{g \in G} p_{g,t} + \ r_t = \ d_{b,t} - uns_{b,t} \qquad \forall b \in B, \forall t \in T \tag{6.60}$$

$$\sum_{g \in G} cu_{g,t} - p_{g,t} \geq d_{b,t}SR - usr_t \qquad \forall b \in B, \forall t \in T \tag{6.61}$$

2. Renewable generation curtailment

$$r_t = RE_t - rc_t \qquad \forall t \in T \tag{6.62}$$

3. Unit commitment

$$cu_{g,t} \leq AV_g b_g IC_g \qquad \forall g \in G, \forall t \in T \tag{6.63}$$

$$p_{gt} \leq cu_{g,t} \qquad \forall g \in G, \forall t \in T \tag{6.64}$$

$$p_{gt} \geq b_g MIC_g \qquad \forall g \in G, \forall t \in T \tag{6.65}$$

$$b_g \in [0,1] \qquad \forall g \in G \tag{6.66}$$

$$p_{g,t}, cu_{g,t} \geq 0 \qquad \forall g \in G, \forall t \in T \tag{6.67}$$

4. Power flow

$$-F^{max} \leq n\left(p_g - d_b + uns_b\right) \leq F^{max} \tag{6.68}$$

$$F^{max} = S_{line} \tag{6.69}$$

where FC_g is the fixed O&M cost of each individual generator g in the system (\$/MWh), MC_g represents the combination of the variable O&M and fuel cost of each generator (\$/MWh), c_{uns} is the unserved demand penalty (\$), c_{sr} is the degraded reserve penalty (\$/MWh),c_{curt} is the cost of curtailed renewable power (\$/MWh), cb_p is the carbon tax (\$/MWh), p_{gt} is the hourly power dispatched from each unit (MW), cu_{gt} is the hourly committed capacity of each unit (MW), r_t is the hourly power dispatched from each renewable generator (MW), rc_t is the hourly curtailed power of each renewable generator (MW), RE_t is hourly available power from each renewable generator (MW), b_g is the binary commitment for generator dispatch, AV_g is the availability of each generator, D_t is the hourly demand (MW), uns_t is the hourly unserved demand, usr_t is the hourly degraded spinning reserve (MW), IC_g is the installed capacity of each conventional generator (MW), MIC_g is the minimum power output of each conventional generator (MW), SR is the system spinning reserve (MW), F^{max} is a vector of the branch power flows (MW), p_g is a vector of power generation at the buses, d_b is a vector of demand at the buses, uns_b is a vector of unserved demand at the buses, n is the node arc matrix relating power injection to branch power flows and S_{line} is the power rating of the branch (MVA).

The objective of the model is to minimise the fixed and variable generation costs, the carbon tax cost, the cost of unserved demand and as well as the reserve penalty cost. Penalties are included in the model to ensure a reserve margin of 10%, supplied by conventional generators only, and a constant supplied demand. A reserve penalty of $1,000 is assumed for this analysis. Penalties have also been included to curtail the production from wind and solar generators when optimal. The unit commitment constraints limit the production of each unit to a reduced capacity based on its forced outage rate. While carbon taxes are not currently implemented for power generators in Nigeria, it has been included in the analysis to evaluate the potential impact of the cost of its penalty on the contribution from renewable sources. Using DBEIS (2016), carbon taxes of $5/MWh and $7.5/MWh are assumed for CCGT and OCGT plants respectively. The transmission line parameters for the Nigerian network used in the model have been obtained from TCN (2017). The power flow is modelled using the direct current OPF (DCOPF) technique (Li & Bo, 2007). While this technique provides less accuracy (~5%) compared to the alternating current OPF (ACOPF) technique due to its assumption of lossless power transfers, the computational speed of solution convergence makes it widely adopted for planning analysis (Overbye, et al., 2004) (Bakirtzis & Biskas, 2003).

6.5.2 Energy Production Costs

The energy production cost analysis is initially performed with the power flow limits imposed on the system, and then a further analysis is performed relaxing the power flow constraints to assess the impact of the transmission network on the system. The high scenario peak demand is used for this analysis.

The generation from hydro stations are dispatched using a monthly scale factor based on historical (2013-2016) monthly generation profiles and calculated as per unit of the peak generation of each month. This is necessary in order to simulate existing monthly production patterns and to better represent the annual resource variability impact on the optimal displacement of conventional hydro generation by cheaper generators. The annual profile of the three hydro generation stations are shown in Figure 6-27. Across the three stations, maximum production occurs between September and November, at the end of rainy season, however, Kainji produces power at a high output level between March and May.

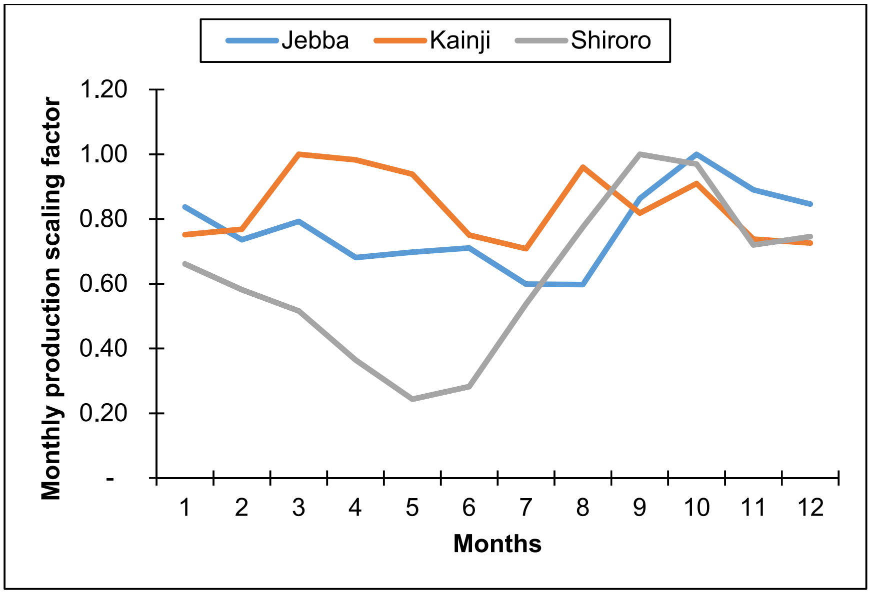

Figure 6-27: Annual generation profile of conventional hydro stations

Having shown that the capacity value decreases non-linearly with an increasing penetration of both renewable resources, the planning model evaluates the cost impact on the grid using the target capacity of each renewable energy source of 5.5GW and 0.8GW for solar and wind, respectively. Three scenarios are evaluated for this analysis, (1) conventional plus renewable capacity additions, (2) conventional plus renewable capacity additions with the carbon tax implemented, and (3) conventional generators only.

A typical hourly generation profile from the unit commitment power flow model is shown for the conventional and renewable energy scenario in Figure 6-28. The coloured area represents the total dispatched generation by type. The uncurtailed capacity is the sum of dispatched capacity, reserve margin and total renewable energy production. The reserve margin is supplied from only the conventional generators. The 'available capacity' here represents the sum of dispatched capacity, reserve margin and curtailed renewable energy production.

Energy production in the early morning and late night is dominated by thermal and hydro generators, with some production from wind overnight. The hydro generators follow the monthly supply patterns shown in Figure 6-27, with a maximum generation limit for each month. The hourly hydro production varies up to the maximum monthly output. The midday sees energy production dominated by the solar generators as a result of the irradiance magnitude in this period. The conventional thermal and hydro generators must supply the reserve margin which sees them 'constrained on' at minimum levels during the middle of the day. The reserve supply constraint results in the curtailment of renewable energy in order to enable the conventional generators supply reserve. The energy curtailed is the gap between the available capacity and uncurtailed capacity i.e. the black and green lines. Maximum curtailment occurs midday when renewable energy production is at its peak. The magnitude of curtailment is influenced by the transmission limits restricting the flow of energy in the system.

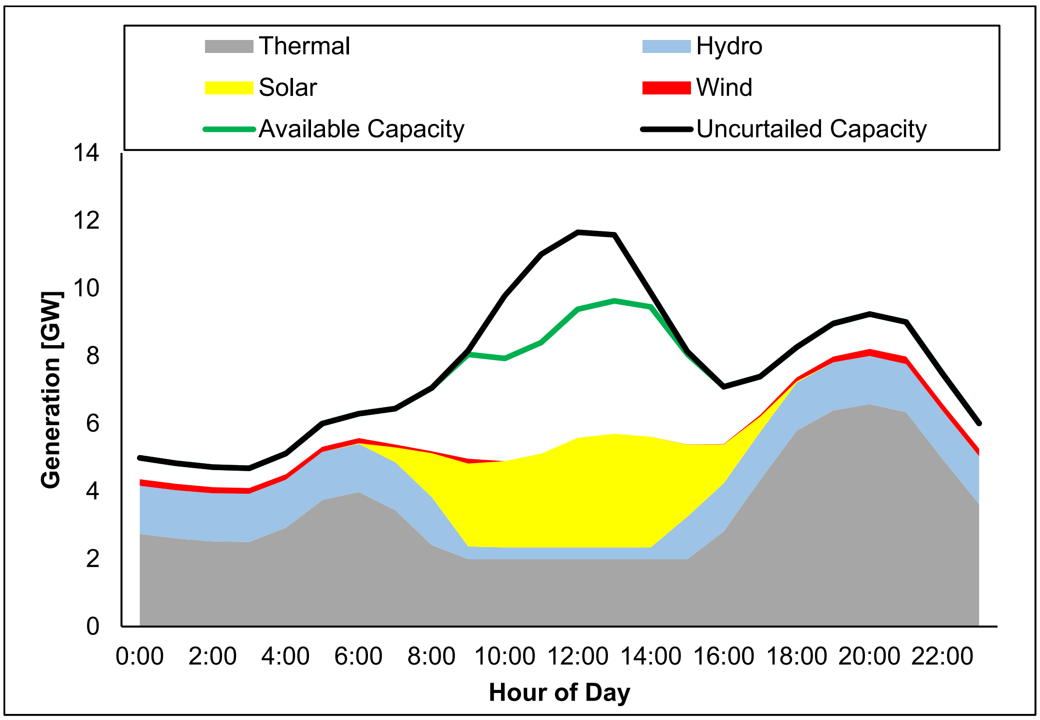

Figure 6-28: Hourly generation profile – 1 day

The pattern of supply for 10 days and annual energy production are shown in Figure 6-29 and Figure 6-30 respectively. The total annual energy supplied in each scenario is 51.4TWh. The energy not supplied (ENS) which calculates the total annual unserved demand is 8.5GWh for each scenario. Unserved demand events occur during the daily peak demand hours between 7-9pm, with the magnitude of ENS determined by the value of the peak demand, as shown in Figure 6-29. In the plot, Days 4 and 5, which have the largest peak demand values, have the highest magnitude of ENS. The seasonal trend reveals 64% of the ENS occurs in the dry season, with 36% occurring in the rainy season. However, the maximum individual unserved demand events occur during the rainy season (May) as a result of the reduction in generation availability from the hydro stations due to lower seasonal reservoir inflows and poor wind production.

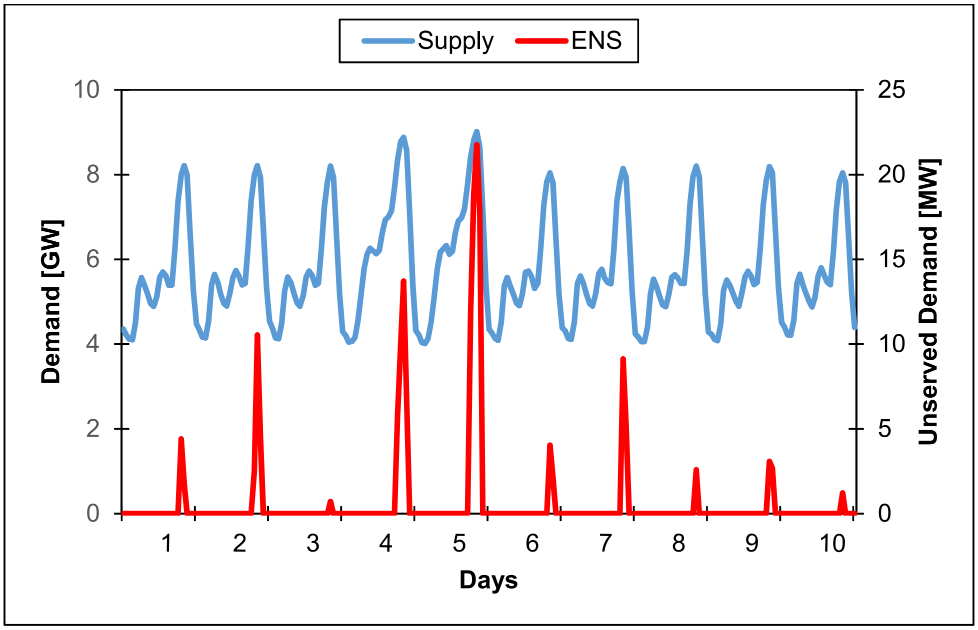

Figure 6-29: Daily Grid Power Supply

With conventional generators only, the contribution by generation technology type is 76% and 24% for thermal and hydro plants respectively. The integration of new renewables resources into the energy mix sees a change in the contribution by technology type, with 61%, 21%, 17% and 1% of the energy supply provided from thermal, hydro, solar, and wind plants respectively. The penalisation of carbon emissions sees a reduction of 33.9GWh (0.1%) in the production from thermal plants, and an increase of 25.7GWh (0.24%), 7.1GWh (0.08%), and 1GWh (0.18%) in the production from hydro, solar and wind respectively, from renewable scenario 1 to 2. The cost minimisation objective sees a reduction in energy supplied from the now more expensive thermal plants, with the displaced energy replaced by the cheaper renewable energy options, of which hydro is the main beneficiary. The poor temporal coincidence between solar generation and peak demand means the cheaper solar generators are not able to take maximum advantage of the opportunity during peak demand afforded by the more expensive thermal generators. The poor annual resource availability and the relatively smaller capacity places a limit on the opportunity for wind generators.

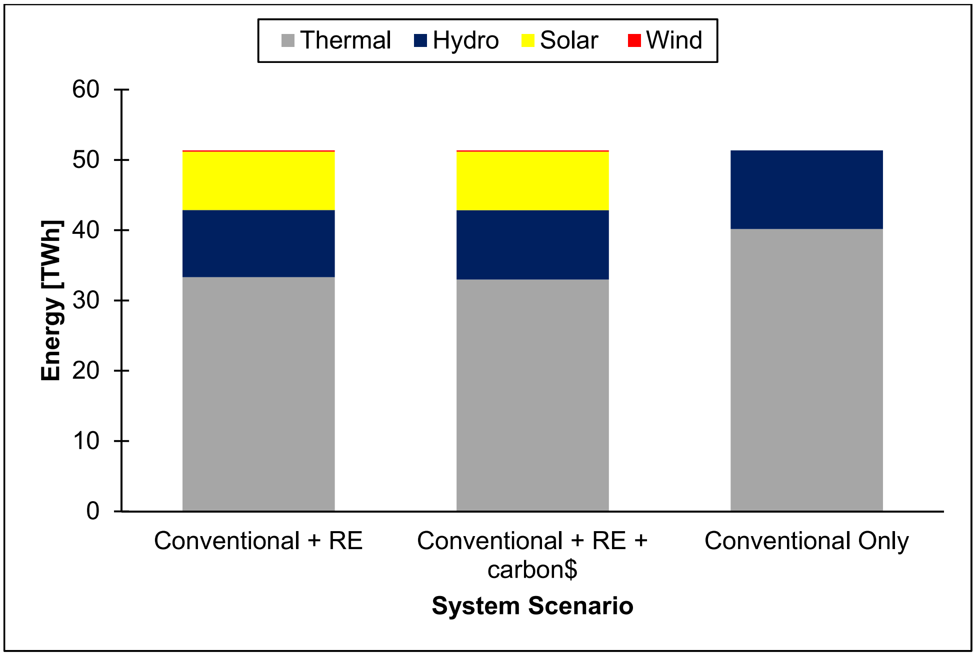

Figure 6-30: Annual Energy Production

The production change observed between renewable scenarios 1 and 2 is positive for the system as it means the implementation of carbon emission penalties will see the displacement of thermal generation by cleaner energy sources. The inclusion of energy storage on the network, which stores cheaper energy during off-peak demand periods and supplies it during peak demand hours, should see an even larger impact on the thermal generation reduction, as the stored energy will bridge the coincidence gap obtained between solar production and peak demand. This will be included as part of future work in the planning model.

The annual energy generation costs are shown in Figure 6-31. The annual cost of energy production with the conventional plants only is $1.26Billion, which sees an increase to $1.27Billion (1%) with the integration of renewable generation and implementation of carbon taxes, and a reduction to $1.1Billion (15%) without carbon taxes. This translates to system production prices of $24.6/MWh, $24.9MWh and $20.9/MWh for the conventional only, scenario 1 renewable, and scenario 2 renewable, respectively.

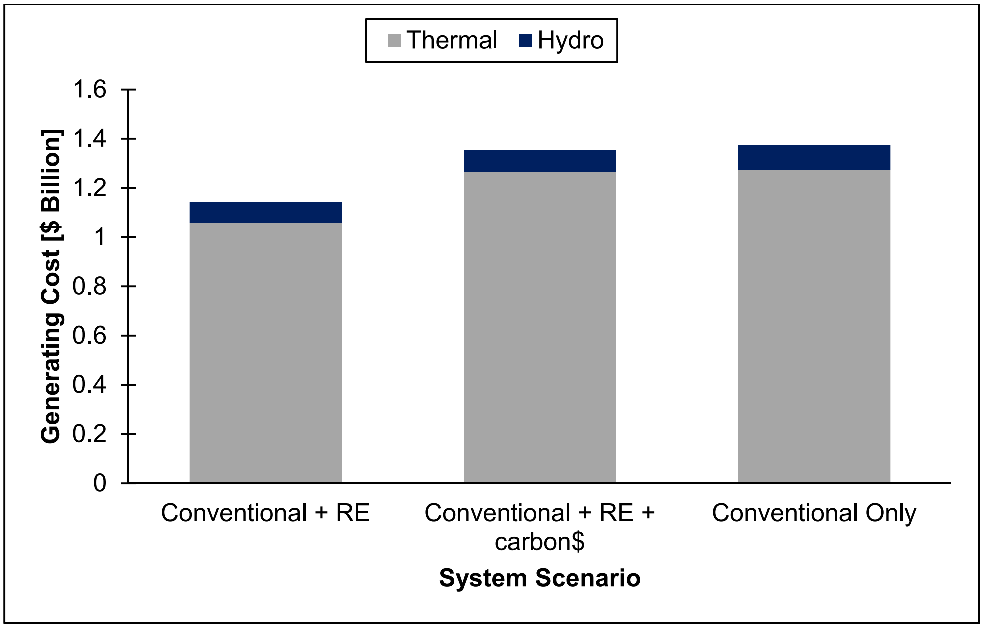

Figure 6-31: Annual Energy Generation Cost

The implementation of carbon taxes introduces a cost of $205 Million to the system after integration with the new renewable sources, for a thermal energy displacement of 33.4GWh, which is expensive ($6,060/MWh) for the amount of fossil energy displaced. The inability of the solar and wind sources to take advantage of the more expensive thermal generators results in a flat increase of the hourly thermal generation cost by the carbon tax. However, the inclusion of carbon taxes was done to evaluate the potential of thermal energy to be offset by cleaner energy sources, which it has shown, but it also means that in isolation carbon taxes will be not optimal in the Nigerian system with constrained renewable sources. The imposition of a carbon tax on energy generation without the resultant effect of cleaner and more efficient energy will result in higher production costs which will be passed on to consumers.

6.5.3 Transmission Constraints

This analysis was conducted with the power flow constraints removed. The grid branch network is presented in Table C. 3. The results for the unit commitment without power flow constraints (UC) and unit commitment with power flow constraints (UCPF) model are presented in Table 6-5. The cost savings from renewable energy integration increases from 15% in the UCPF model to 27% in the UC model. The absence of transmission line limits sees an increase in the energy supplied (i.e. no ENS) in the UC model as compared to the UCPF model, and a reduction in the curtailment of renewable energy from 1.7TWh to 0.02TWh. With only the conventional generators providing the reserve margin, curtailment of renewable generation occurs on the network to ensure the conventional generators can meet the reserve requirement, which explains why curtailment persists in both models. The magnitude of curtailment in the UCPF model is driven by the system's congestion, particularly in the southern part of the network (L70, L68, L21), restricting the transmission of solar energy to the northern load centres during the day, and the export of wind energy from the northern load centres (L55, L59, L90, L26) to the south during the night. Locational demand is met at the renewable energy generation buses however transmission bottlenecks restricts the export of excess energy to locations with unserved demand.

Table 6-5: System Performance by Model type

Model	Cost ($ Billion)	ENS (GWh)	Curtailment (TWh)
UCPF			
Conventional	1.26	8.47	
Conventional + RE	1.07	8.47	1.7
UC			
Conventional	1.15	0	
Conventional + RE	0.84	0	0.02

Figure 6-32 shows the monthly energy curtailment profile. Typically, the magnitude of curtailment is dependent on demand levels, with higher levels of curtailment occurring when demand is low, and vice versa. The seasonal production from renewable sources also affects the magnitude of curtailment e.g. the expected curtailment of solar generation during winter will be significantly lower than that of summer due to lower irradiance levels. Both effects are observed in the model results. Maximum curtailment occurs in the dry season months due to higher seasonal irradiance levels, however, the occurrence of peak demand between February and April sees a reduction in solar curtailment. A further reduction in solar curtailment occurs during the rainy season, due to seasonal irradiance effects. However, the reduction in demand between June and August sees an increase in curtailment. Similarly, for wind curtailment, maximum curtailment occurs in the dry season (February) due seasonal effects, and a reduction in wind curtailment accompanies the lower wind capacity factors obtained in rainy season.

These effects are more prominent in the UCPF model in comparison to the UC model, although the effect is still observed in the UC model. The impact of transmission line constraints can be observed in the dry season curtailment patterns of both models. In the UCPF model, a decrease in curtailment is accompanied by an increase in demand from the northern solar generators, a portion of the otherwise curtailed energy due to transmission constraints is now consumed by the increased cooling demand at those buses. The magnitude of curtailment in the UCPF model is due to the transmission bottlenecks restricting the supply of excess energy from the buses with renewable generators.

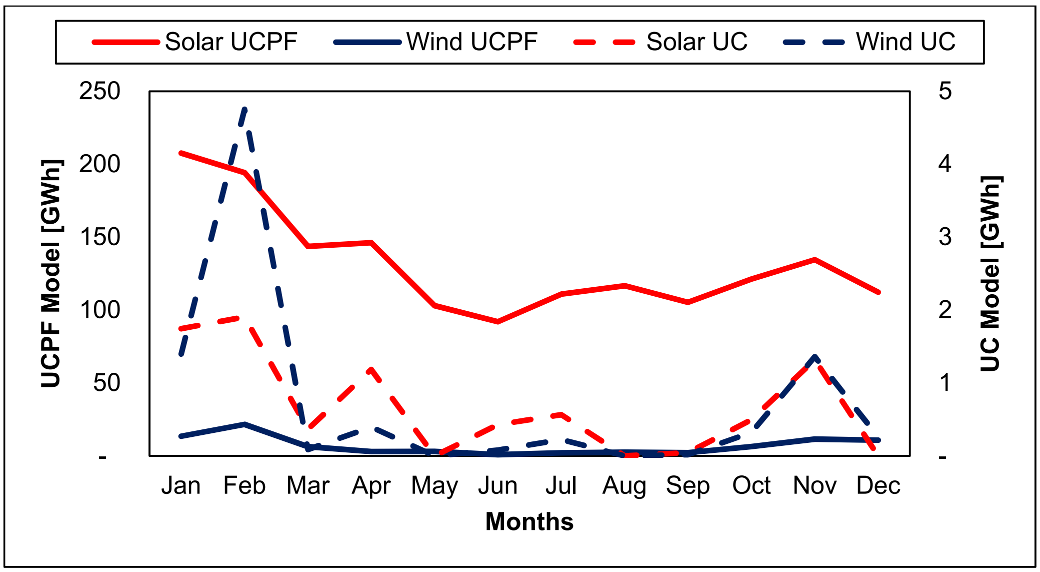

Figure 6-32: Total monthly energy curtailment

6.5.4 Current Energy Supply

The analysis provided in section 6.5.2 focused on the future energy supply outlook with a substantially expanded conventional generation portfolio. The focus of this section is to evaluate the current energy supply situation in the country. For this analysis, availability of conventional generators is set to 40% to obtain a total generation capacity of 5GW; actual maximum recorded generation is 5.2GW, and the average available capacity is even lower (Nigeria Electricity System Operator, 2018).

The UCPF model is used to evaluate the impact of the target renewable generation vis-à-vis the current generation portfolio and the results are presented in Table 6-6. With the maximum generation capacity of conventional generators set to 5GW, it means that any demand above this value cannot be met by the conventional generators. When demand exceeds this maximum generation capacity, at night time extra energy is supplied from the wind generators, and during the day from solar generators. The renewable generation benefit provides a 10% increase in energy supply. The unsupplied demand events result in an ENS of 10.9TWh, with a reduction of 35% to 7.1TWh, as a result of an increase in supply from renewable generators. The maximum capacity limits imposed on all conventional generators results in a reduction of available capacity from cheaper conventional generators, resulting in the more expensive generators supplying the energy difference. This leads to an energy production cost of $1.3Billion, with a reduction of 18.5% to $1.1Billion, with the integration of renewables. The reduction in generation capacity also results in breaches of the reserve margin, which reflects vulnerable system conditions, with the network operating without reserve when the demand exceeds the maximum generation capacity. It results in a cost of $32.6Million, which is reduced to $21.5Million with the integration of renewables.

Table 6-6: Current System Supply

	Energy (TWh)		Cost ($Billion)	
Scenario	Supply	ENS	Supply	Reserve Penalty
Conventional	40.3	10.9	1.3	0.0326
Conventional + RE	44.2	7.1	1.1	0.0215
% Difference	10	-35	-18.5	-34

6.6 Summary

This chapter showed the value of the generated time series demand data in assessing the benefits of renewable integration in Nigeria. It presented a system reliability analysis showing the capacity value of wind and solar generation to the network. It also showed the system cost benefit of renewable energy using an operational network analysis.

Chapter 7
Discussion and Conclusion

7.1 Thesis Summary

Chapter 1 gave an introduction, set out the scope and objectives of the research, presented the thesis statement and contribution to knowledge.

Chapter 2 presented an overview of power systems with a description of its various structures. It described the key considerations for power systems planning and also presented planning approaches used in traditional and restructured electricity markets. Basic concepts of demand analysis along with a description of demand forecasting techniques were also discussed.

Chapter 3 described the electricity industry in Nigeria with an overview of key market participants. It discussed the key segments in the power delivery value chain and highlighted the issues with the distribution network. It showed how the poor electrification rate along with losses in the distribution sector negatively impacts economic growth and industrialisation. It described the challenge of estimating peak demand due to the extensive suppressed demand and the lack of reliable time series demand data from the grid due to load shedding. It then discussed the need for weather sensitive methods in demand studies for Nigeria.

Chapter 4 presented a bottom-up model for generating weather sensitive electricity demand data for Nigerian households. It started with a description of a household survey undertaken to develop the household profile database used in the model. It described the appliance and AC sub-models used to simulate household energy consumption. Results from the model were validated against measured data from Nigeria.

Chapter 5 presented a method for estimating peak demand for Nigeria. It described the socioeconomic data used for developing representative regional and national household profiles. It assessed the performance of the satellite reanalysis weather data used for simulating ambient conditions. A sensitivity assessment of a temperature increase of 1°C across all locations simulated is shown to have a minor effect on total energy consumption due to low AC ownership. The result of the construction of national time series demand data using the residential model output, and non-domestic demand estimates from a previous national load study, were also discussed. Results of the residential and aggregate peak demand estimates were compared against results from previous studies.

The value of time series demand data was shown in Chapter 6, which presented an evaluation of the future energy demand-supply balance in Nigeria. It assessed the benefit of renewable energy by evaluating the potential of solar and wind energy generation based on the renewable energy masterplan of the government. The results of the time profile assessment of demand and variable energy resources were shown. Results of the capacity value and system reliability impact assessment were presented, along with a projection of the energy production cost benefit that will be gained from diversifying Nigeria's energy portfolio.

7.2 Discussion of Results

7.2.1 Peak Demand Estimates

Non-simultaneous peak recorded electricity demand in Nigeria is currently 5.6GW, however due to constant load shedding and generation supply constraints, a demand pattern is unavailable. Peak electricity demand estimates of 5.5GW, 6.6GW and 9.1GW have been generated for low, medium and high electrical appliance saturation scenarios. Without any network level study available on the impact of weather on electricity demand in Nigeria, accompanying weather sensitive demand curves have been constructed for each demand scenario, with an average load factor value of 60%, which compares well to values from global networks. The total estimated energy consumption for the low, medium and high scenarios are 30.6TWh, 37.1TWh and 49.5TWh respectively.

The total estimated residential energy consumption for the low, medium and high scenarios are 12.5TWh, 15.3TWh and 21.9TWh respectively. For residential cooling energy consumption, the low, medium and high scenario estimates are 0.5TWh, 0.8TWh and 2.4TWh respectively. The residential energy consumption per customer estimates in the low, medium and scenarios are 2.3MWh, 2.8MWh and 4.0MWh respectively.

Energy from cooling demand was shown to contribute 4%, 5% and 11% to the total residential electricity demand, in the three socioeconomic scenarios used for this study. Increased cooling demand has been shown to potentially influence the demand pattern with peak demand occurring during the dry season and reduced demand observed during the rainy season. AC appliance saturation increases resulted in the rise of the estimated annual cooling energy consumption by 63% between the low and medium scenario, and 186% between the medium and high scenario. National peak demand is expected to occur in the dry season, with the DisCos all experiencing peak demand between the months of February and April, with the exception of Kano, which has peak demand occurring between April and June. A temperature increase of 1°C was found to have a minor effect (4%) on total energy consumption due to the current low AC ownership level in the country, however it resulted in a 26% increase in cooling energy consumption.

Domestic sector peak demand estimates presented in this research have been limited to residential customers currently connected to the distribution networks. Considering the large number of unmetered customers, residential customers using their premises for commercial activities, and unconnected households, the customer population used in this analysis is the base estimate. The model can be used in forecasting electricity demand for projected customer population growth and extended to include unelectrified households. The socioeconomic model can also be extended to increase the current electrical appliance suite along with adjustments to the appliance efficiencies, for energy efficiency studies using a bottom-up approach. The weather model enables the study of the influence of different climate scenarios on electricity demand in Nigeria. The model can be applied to individual distribution networks in the country for high resolution electricity demand studies. The model can also be used to study electricity demand in developing countries with similar challenges as Nigeria.

Prior network assessments and energy adequacy studies for Nigeria have been limited by reasonable peak demand and time series estimates. The current investor template used by NERC (2015) assumes a fixed annual demand value for each DisCo, which is not the case as there is constant variability in demand across the companies. Energy researchers and investors seeking off-grid solutions for rural communities are also constrained by the lack of demand data, and the inability to quantify the available demand can be detrimental to any potential investment. The frequency of load shedding experienced on the network also means that traditional methods of demand forecasting are inadequate to use for projections. The availability of load time series and curves from this model enables its use for power planning studies in networks affected by load shedding and power cuts. The data can then be used in system planning analysis to evaluate transmission investment and to quantify the impact of different transmission expansion scenarios.

7.2.2 Energy Supply

With the ongoing network expansion of the Nigerian grid, a reliability analysis is required at every stage to determine quantifiable improvements necessary to guarantee power supply adequacy. Deterministic approaches such as the N-1 criterion and the system reserve margin currently used by the system operator must be complemented by probabilistic reliability evaluations that weigh the uncertainty in energy contributions from generators.

In wholesale energy markets, competition between conventional generators incentivises the optimal performance of generator units and ensures availability during peak demand periods to guarantee profits. However, in a purchasing agency structure, long term power purchase agreements without reliability performance covenants built in them might discourage the optimal performance and availability of generators as the off-taker will be required to purchase power whenever it is available. The recent study by Oyedepo, et al. (2015) has revealed suboptimal generating unit availability indicators for selected power stations in Nigeria. The regulator must mandate a baseline LOLE and monitor the individual contributions of units to this baseline value by ensuring adherence to minimum unit availability indices using IEEE standard -762 (IEEE, 2012) as a guide. The cost of ENS borne by consumers when unwanted system events occur as a direct result of unacceptable levels of unit availability should be passed on to the generators by the regulator in the form of penalties. The system LOLE of an estimated 439hours/year explains the frequency in load shedding and blackouts currently being observed by consumers. The LOLE for the current system reveals higher dry season probabilities of load loss with minimal values obtained in the dry season. In the operational system model, the ENS was shown to have a higher occurrence in the dry season compared to the rainy season, however the current system configuration is at its highest risk during the rainy season due to the reduction in availability from hydro generation.

The demand profiles used in similar studies for evaluating solar capacity in mature electricity networks have been characterised by substantial midday demand and a high correlation with daily solar peak output, resulting in more significant solar capacity values observed (Madaeni, et al., 2012), (Dent, et al., 2016). With the current renewable energy focus to bridge the energy supply gap in developing countries (International Energy Agency, 2014), demand assessments will be required in those countries to quantify the impact of the energy from time constrained renewable energy sources on interim and long-term network reliability. For countries with similar demand profiles to Nigeria, and in the absence of energy storage infrastructure (Edwards, et al., 2017), solar capacity benefits will be realised gradually over a long term as the contraction of demand towards the midday leads to a higher coincidence with solar generation output. In the short term, solar energy supply should be prioritised for midday demand peaking customers such as industrial and commercial customers, as the capacity value is higher for non-domestic demand compared to aggregate demand. The solar capacity value results for the aggregate non-domestic demand are comparable to similar studies performed for networks with notable midday peak demand, with an initial high value and a rapid decrease with solar capacity increments (Munoz & Mills, 2015). The increase in generation capacity and adequacy should result in changes in the time series profile of demand, as increases due to consumer adjustments to improved power supply will be expected to redefine its current temporal characteristics. Potential midday cooling demand increase from commercial and residential customers is expected to be a substantial driver of this change. Another factor which can affect the temporal feature of aggregate grid demand is the impact of embedded renewable energy projects in DisCo locations and the increased penetration of domestic PV installations in customer locations (Thomson & Infield, 2007).

With a high temporal coincidence with daily peak demand, wind generation makes a higher contribution to system reliability and generation adequacy than solar, however, the range annual production from wind is seasonally constrained leading to lower generation during the rainy season. The mean wind speeds observed of between 5.0-6.1m/s will require WECS in Nigeria with a lower rating and cut-off speed compared to the one used in this study, that can yield higher capacity factor values than the 9.5-12.0% aggregate annual mean values obtained. The hours of production of at least 50% of the aggregate rated installed capacity of wind is less than 1% of the total hours of the year, limiting its potential to contribute to generation adequacy.

Historical monthly aggregate hydro generation data reveals minimum production is observed over the rainy season months, with peak generation observed between September and October.

While the timeline and locations for the construction of solar projects are not available, this study has incorporated a spatial element to measure the potential of solar contribution from each DisCo. From the irradiance and capacity factor values, the potential for solar energy generation is higher in the northern regions compared to the southern regions. With a limited interim solar capacity value at the national level, optimal siting of commercial solar projects is a necessity for the Nigerian network.

Conventional generation capacity reductions were shown to result in an increase in wind and solar capacity values. With the current levels of generation unit unavailability across the network, generation adequacy and system reliability will be improved with renewable generation integration. The reduction in capacity factor values should also impact any future capacity factor payments to renewable energy generators, as equal payments with increasing capacity installations will lead to overcompensation in comparison with the diminishing impact on system reliability (Dent, et al., 2016).

The energy production cost analysis was performed for the future and current energy markets to highlight the benefits of renewable integration. In the future energy outlook, decongestion of the transmission network was shown to increase the energy cost savings by 27%. The study also showed the benefit of an unconstrained transmission network with a significant reduction in renewable curtailment and ENS occurring between the UC and UCPF models. The imposition of carbon taxes on thermal generators saw a reduction in their energy production, and an increase in energy output from cleaner energy sources. While the temporal mismatch between peak demand and solar output limits the ability of solar generators to produce more energy with the imposition of carbon taxes, the increased tax revenue of $205Million can be used to fund renewable energy subsidies. A potential change in the temporal demand profile with peak demand occurring earlier will see a gradual reduction in energy costs as renewable producers are able to contribute more energy during peak demand periods. The cost analysis revealed a 15% ($231Million) reduction in energy costs with the integration of solar and wind generation, a 23% reduction in thermal energy production, and a better diversified energy portfolio, for the proposed renewable capacity targets of the government's renewable action plan.

For the current energy outlook, a maximum generation capacity of 5GW was used to represent the current system. Demand above this capacity resulted in load shedding, with an ENS of 10.9TWh, which agrees with the IEA (2014) estimate of 11.4TWh off-grid generation for Nigeria. The ENS is reduced by 35% with the integration of the target renewable capacity for Nigeria. Renewable integration sees an increase in the energy supplied by 10%, and a reduction in the energy production cost of 18.5%. The system is vulnerable to outages and collapses when operating without reserves, and the integration of renewable energy sees the system security improved with a reduction of the reserve penalty by 34%. While the impact of renewable energy in the future energy outlook is positive, the potential benefits from renewables in the current energy market is even more substantial.

According to NESI (2017), with the power sector is currently losing an estimated $2.5Million daily due to generation capacity unavailability, the integration of renewable energy can play a significant role in reducing this deficit. With government reportedly spending an estimated $1.6Million daily on fuel subsidies (Vanguard, 2017), and with significant off-grid generation powered by expensive diesel generators (NOIPolls, 2015), (NESI, 2015), the cost saving benefit of renewable energy will see a reduction in government expenditure with the fuel subsidy funds channelled to better use. The temporal coincidence between solar energy and non-domestic demand will see improved power supply for this sector encouraging commercial activities and reducing the cost of producing goods and services in the country. Carbon and noise pollution will also be reduced significantly with energy supply from cleaner sources.

The system reliability benefits and energy production cost reduction shown in the results reveals that renewable energy can play a significant role in bridging the energy supply gap.

7.2.3 Limitations

The bottom-up appliance modelling approach used as the foundation for this study is dependent on the accurate capture of household activities to ensure the demand patterns generated from the model are a good representation of actual demand. For a country as culturally diverse as Nigeria, and with its estimated population of over 180 million people, the household diary used for this research is limited in its ability to accurately replicate all households in Nigeria. However, in the absence of a national time of use database, the diary as constructed in the survey sought to capture as best as possible households' electricity consumption patterns under constant power supply conditions. While measured domestic electricity readings would have been the best option to use for this study, the financial and manpower requirements necessary for such a project were beyond the scope of this research. In any case, it would also require measurements in locations across the country that are not prone to load shedding, as measurements obtained during periods of power supply are likely to be inflated due to demand shifts to those periods; which adds another level of challenge to the project. Underrepresentation of demand in any period has the potential of reducing the load factor, as it reduces the average demand generated for the household. While the diary data appears to indicate some underrepresentation of weekday midday household activities as shown in section 4.2.4, it is a valuable resource as a first step in a series of steps in building a model capable of evaluating electricity demand and energy consumption in a developing country.

The approach used for modelling the thermal response of buildings was to enable a reasonable capture of ambient effects across occupied houses simulated in the model. Simplifications were made in modelling flats and single room apartments which are part of terraced houses or apartment blocks, as only external apartments have been treated in this model. The absence of internally located apartments in the model might tend to overestimate the overall effect of external temperature on cooling demand in flats and single room apartments. The impact of inter building shading effects were also not represented in this model, which could also increase the building energy demand.

The appliance ratings used in the model have been obtained from an energy efficiency study done in one state in Nigeria and could include a bias in the appliance power demand. Efficiencies of appliances have been left unchanged in the scenario analysis, even though as socioeconomic conditions improve and coupled with advancements in technology, electrical appliances have been shown to increase efficiency (Office for National Statistics, 2015). The ACs have been modelled with a power rating of 1hp and might explain the lower contribution of cooling to the total energy consumption. Future work would explore the impact of changes to the appliance power ratings on energy consumption, but it would likely scale broadly with rating. R3 and R4 customers are typically estates occupied by residential customers in the higher income class. Modelling appliance ownership for customers in this tariff class is challenging due to diversity in appliance ownership for this class of customers and a higher penetration of high power rated appliances. An attempt has been made to estimate the demand of individual households that occupy representative estates built into the model by using appliance ownership data from the survey and increasing ownership in the medium and high scenarios. While this attempt might underestimate the demand for these tariff classes, they contribute only about 5% to the total residential energy consumption in Nigeria (NERC, 2015), therefore limiting the impact on the model results. The model also relies on appliance ownership data from the National Bureau of Statistics (NBS), however surveys executed by the NBS include unelectrified respondents, which has the potential of underestimating appliance saturation.

The population distribution method used to allocate residential customers to the states within the DisCos is based on a 2009 study undertaken before the deregulation of the electricity market, therefore updated population numbers will be required from the DisCos to improve the accuracy for state peak demand.

Chapter 4 discussed the bias in the weather data used in the model, and the conclusion was reached that a weather bias correction study will need to be undertaken to improve the simulation of ambient conditions across the country. The model has not included the effects of other weather variables such as humidity, rainfall and wind speed since peak demand estimates were the focus of the current study and require the variables with the strongest correlation to electricity demand (Hor, et al., 2005). The reduction in cooling energy during the rainy season shown in this study is a function of the seasonal temperatures only.

The comfort level used in this model is based on a residential survey of preferred thermal comfort temperature performed in one state, which in practice might vary across the states. Influences such as intermittent power supply, electricity cost, health and even weather might be deterrents in using ACs, as shown from the survey results. Since the aim of this work is to simulate uninterrupted residential energy consumption in Nigeria, the thermal comfort range selected for this model is deemed sufficient to represent thermal comfort choices in a constant power supply environment. For location specific studies, the thermal comfort levels can be adjusted to simulate cooling demand within that network location.

Load curve construction has relied on non-domestic sector demand estimates that were independent of weather impact. While industrial loads are typically classified as base loads independent of weather variations, the high penetration of ACs among commercial customers for space cooling means commercial demand will also have seasonal variations (Sullivan, 1977).

The PVs used for modelling solar production are commercial ground installations and not roof mounted PVs which are more dominant in Western countries (Thomson & Infield, 2007)., however without a similar level of penetration in Nigeria, the renewable energy master plan has guided the presented approach.

There is also a tendency for the production from wind to have been underestimated due to the V90 turbine used in this analysis.

7.2.4 Recommendations for Future Work

Demand and renewable energy simulations used weather data, and preliminary analysis has revealed bias in the datasets employed. Future work will require a bias correction exercise performed for each weather dataset using measured data from Nigeria.

The thermal comfort levels used for each state in the study was based on a range of values obtained from a study done in one location in Nigeria. The historical effects of inefficient power supply and load shedding being experienced on the network has been found to affect the current AC usage rates, and in essence, the acceptable thermal comfort levels. The improvement of power supply across the network and improvement in geopolitical socioeconomic conditions should see a change in both ownership and usage of ACs. Future work will see the inclusion of thermal comfort preferences, for people living in different locations across the country, in the model.

Unavailable data on the penetration of ACs by appliance power rating has led to the current assumption of 1hp (745W) used in the model. Further work is required to assess the impact of higher rated ACs on the peak demand estimates.

Future work will require the assessment of the influence of weather on energy consumption in Nigeria's non-domestic energy sector, especially in the commercial sector that requires substantial cooling energy (Ürge-Vorsatz, et al., 2015).

The wind turbine model used for analysis in this study is not optimal for the Nigerian wind regime and a further study will be required to perform a disaggregated analysis for the optimal turbine production of wind energy across Nigeria.

7.3 Concluding remarks

This research set out to generate reliable peak demand estimates and time series data for Nigeria, which it has done. As Nigeria aims to expand its network and chart a new energy future for itself, robust assessments will be required at various levels on the network, and such work will be aided by qualitative data such as the output generated from this research. The energy shortage challenge is not insurmountable and a future where the words of Isaiah in (Crossway, 2001) are established is on the horizon.

"The people who walked in darkness have seen a great light" Isaiah 9:2

Appendix A
Socioeconomic data

THE UNIVERSITY *of* EDINBURGH

Domestic electricity consumption trends in Nigeria Questionnaire

This survey is part of a research project funded by the University of Edinburgh and in collaboration with Energy Markets and Rates Consultants (EMRC) Nigeria.

This survey aims to capture information to help understand electricity consumption trends of households in Nigeria. It seeks to gather data about household occupant behaviour patterns based on lifestyle and electrical appliance ownership. Results from this survey will help answer questions about Residential energy demand in Nigeria and assist with the planning to ensure constant power supply to all Nigerian households.

Your participation in this survey is completely voluntary.

NB: All questions in Section D should be answered assuming there is constant power supply for 24 hours.

A. Household Classification

1. **Which Distribution Company supplies your home electricity?**
   ____

2. **What is your Residential Tariff Class?**
   ☐ R1 ☐ R2 Single Phase ☐ R2 Three Phase ☐ R3 ☐ R4

3. **What type of Meter do you use?**
   ☐ Post-paid ☐ Pre-Paid ☐ No Meter Installed

4. **What type of Settlement do you live in?**
   ☐ Rural ☐ Urban

5. **What type of Housing unit do you live in?**
   ☐ Self-Contained
   ☐ Room and Parlour
   ☐ Flat in Block of Flats
   ☐ Semi-Detached House
   ☐ House on a Separate Yard (Detached House)

6. **How many Bedrooms does your Housing unit have?** ___________

7. **Which alternative energy source does your household use when there is a power outage?**
   ☐ Generator ☐ Solar Installation ☐ Inverter ☐ None of the Above

B. Household Appliances

Please write **Yes or No** to indicate which of the listed appliances you own

Appliance	***Do you own any of these appliances?***
Fan	
Air conditioner	
Refrigerator	
Freezer	
Fridge-Freezer	
Microwave Oven	
Electric Kettle	
Water Heater	
Electric Cooker	
Television/Radio	
Laptop/PC	
Washing Machine	
Electric Iron	

2

C. Household Activity
What time do these activities happen in your house on **Weekdays (Mon- Fri)**?
For example, What time do you go to sleep at night? 8am

- **a)** Going to sleep at night ______
- **b)** Having a bath in the morning ______
- **c)** Having a bath at night ______
- **d)** Cooking in the morning ______
- **e)** Cooking in the afternoon ______
- **f)** Cooking in the night ______
- **g)** Watching Television in the morning ______
- **h)** Watching Television in the afternoon ______
- **i)** Watching Television in the night ______
- **j)** Washing your clothes ______
- **k)** Leaving for work ______
- **l)** Returning home from work ______

What time these activities happen in your house on **Weekends (Sat-Sun)**?
For example, What time do you cook in the afternoon? 3pm

- **a)** Going to sleep at night ______
- **b)** Having a bath in the morning ______
- **c)** Having a bath at night ______
- **d)** Cooking in the morning ______
- **e)** Cooking in the afternoon ______
- **f)** Cooking in the night ______
- **g)** Watching Television in the morning ______
- **h)** Watching Television in the afternoon ______
- **i)** Watching Television in the night ______
- **j)** Washing your clothes ______
- **k)** Leaving the house ______
- **l)** Returning home ______

1.

D. Household Activity patterns (Grid Supply)

Please answer the questions in this section assuming there is 24 hours UNINTERRUPTED electricity supply to your home.

a) Sleeping Activity

1. Which cooling appliance is used in your house while sleeping?
   ☐ Fan ☐ Air Conditioner ☐ None of the Above

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2. With constant power supply, how frequently do you use the Air Conditioner while sleeping?
   ☐ Never
   ☐ Rarely
   ☐ Sometimes
   ☐ Often
   ☐ Very Often
3. Reasons for not using Air Conditioner?
   ☐ Weather ☐ Cost of Electricity ☐ Health ☐ Other
4. Average hours of sleep on **Weekdays (Mon-Fri)**
   ______
5. Average hours of sleep on **Weekends (Sat-Sun)**
   ______

b) Bathing Activity

1. Average number of times that people in your house bath a day
   ______
2. Method of heating bath water
   ☐ Electric Kettle ☐ Water Heater
   ☐ Boiling Ring ☐ None of the Above
3. With constant power supply, how often do you bath with hot water?
   ☐ Never
   ☐ Rarely
   ☐ Sometimes
   ☐ Often
   ☐ Very Often

c) Cooking Activity

1. Is the Electric Cooker used for cooking?
   ☐ Yes ☐ No
2. Average number of meals prepared a day with the Electric Cooker?
   ______
3. How many times a day do you use your Microwave Oven?
   ______

d) Entertainment Activity

1. On the average with constant power supply, how many hours do you spend watching Television on a **Weekday (Mon-Fri)?**
   ______
2. On the average with constant power supply, how many hours do you spend watching Television on a **Weekend (Sat-Sun)?**
   ______

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3. How do you switch off the Television
   ☐ Remote control ☐ Mains ☐ Smart TV

e) ***Laundry Activity***

1. Is the Washing Machine the main appliance used for laundry?
   ☐ Yes ☐ No
2. How many times a week is the laundry done in your house?
   ____

f) ***Lighting***

1. Which type of light bulb do you use?
   ☐ Regular bulbs ☐ Fluorescent Tubes ☐ Energy Saver

E. Household Activity patterns (Alternative Energy Source)

*When there is **no power supply** and you generate your own electricity, which appliances do you use with the different power sources? (Please tick to indicate)*

Appliance	***Generator***	***Solar***	***Inverter***
Fan			
Air conditioner			
Refrigerator			
Freezer			
Fridge-Freezer			
Microwave Oven			
Electric Kettle			
Water Heater			
Electric Cooker			
Television/Radio			
Laptop/PC			
Washing Machine			
Electric Iron			

F. Self-Generation Supply

1. On the average, how much do you spend on fuel weekly?
   ____
2. On the average, how many hours a day do you use your generator?
   ____
3. On the average, how many times a day do you experience power cuts?
   ____
4. On the average, how long do the power-cuts last for? (Hours)
   ____
5. On the average, how many hours do you have power supply daily? (Hours)
   ____

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G. Household Information

1. Which State do you live in?
   ____
2. Including yourself, how many people live in your house?
   ____
3. How many people in your house fall in these age categories?
   Children under 9 ☐ Young people aged 10-17 ☐ Adults aged 18-84 ☐
   Adults' aged 65-74 ☐ Adults aged 75+ ☐
4. Number of working occupants (Please classify children in school as working occupants)
   ____

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Table A. 1: Geopolitical Mapping of Distribution Companies

Distribution Company	State	Geopolitical Zone
AEDC	Abuja FCT	North Central
	Kogi	North Central
	Nassarawa	North Central
	Niger	North Central
BEDC	Delta	South South
	Edo	South South
	Ekiti	South West
	Ondo	South West
EKEDC	Lagos	South West
EEDC	Abia	South East
	Anambra	South East
	Ebonyi	South East
	Enugu	South East
	Imo	South East
IBEDC	Kwara	North Central
	Ogun	South West
	Osun	South West
	Oyo	South West
IKEDC	Lagos	South West
JEDC	Benue	North Central
	Plateau	North Central
	Bauchi	North East
	Gombe	North East
KDEDC	Kaduna	North West
	Kebbi	North West
	Sokoto	North West
	Zamfara	North West
KEDC	Jigawa	North West
	Kano	North West
	Katsina	North West
PHEDC	Akwa Ibom	South South
	Bayelsa	South South
	Cross River	South South
	Rivers	South South
YEDC	Adamawa	North East
	Borno	North East
	Taraba	North East
	Yobe	North East

Table A. 2: Appliance Saturation by Geopolitical zone (NBS, 2016)

Appliances	North Central	North East	North West	South East	South West	South South	Urban	Rural	Nigeria
Electric Cooker	3.1	0.6	1.7	2.2	5.5	5.2	5.8	1.7	3.4
Fridge	16.6	8.6	5.9	22.6	34.8	23.5	33.3	9.6	19.2
Freezer	4.7	0.8	3.0	13.5	19.6	15.4	18.6	4.7	10.4
Air Conditioner	0.7	1.1	0.8	3.6	5.9	3.1	5.1	1.0	2.6
Washing machine	0.5	0.3	0.3	2.0	2.4	2.8	3.0	0.5	1.5
Tumble Dryer	0.0	0.0	0.1	0.2	0.2	0.0	0.2	0.0	1.6
Fan	37.5	18.5	18.4	58.8	72.1	71.6	77.2	29.9	49.0
Radio	58.4	72.3	77.1	62.2	51.8	51.1	56.0	64.7	61.2
Cassette Recorder	12.2	10.9	7.5	5.7	5.6	11.6	11.1	7.5	9.0
Hi-Fi	2.3	0.4	0.8	9.5	8.2	11.0	11.0	2.6	6.0
Microwave	1.0	0.2	0.5	2.6	6.1	5.3	6.0	0.9	3.0
Iron	34.9	29.8	19.3	45.8	56.1	56.6	63.9	26.7	41.8
Television	45.5	20.6	21.3	59.9	69.0	70.1	77.3	31.9	50.2
PC	4.1	2.0	2.1	5.4	9.6	5.2	8.3	2.5	4.8
DVD player	34.3	19.3	14.6	51.4	54.5	50.7	58.7	25.1	38.7
TV Decoder	9.7	6.8	6.0	12.0	12.7	8.0	15.5	4.7	9.0
Mobile Phone	76.6	60.6	67.9	86.8	88.0	86.0	89.5	71.7	78.9

Appendix B
Peak Demand Results

Table B.1: R1 Tariff Class ADMD Estimates

Distribution Company	State	Customers	Scenario ADMD (W) Low	Medium	High
AEDC	Abuja FCT	1,475	219	917	1039
	Kogi	3,286	234	678	912
	Nassarawa	1,130	233	592	912
	Niger	751	228	487	698
BEDC	Delta	1,313	229	765	890
	Edo	1,524	223	1035	1129
	Ekiti	180	218	397	579
	Ondo	640	233	459	598
EKEDC	Lagos	-	229	997	1048
EEDC	Abia	546	214	601	697
	Anambra	37	235	647	742
	Ebonyi	808	224	368	669
	Enugu	1,021	240	650	655
	Imo	1,563	236	492	631
IBEDC	Kwara	-	232	576	693
	Ogun	2,583	236	488	669
	Osun	26,042	234	531	713
	Oyo	23,618	219	584	652
IKEDC	Lagos	-	235	999	1048
JEDC	Benue	4,962	233	612	950
	Plateau	10,300	236	670	950
	Bauchi	6,794	226	345	589
	Gombe	5,564	239	337	674
KDEDC	Kaduna	97	221	513	668
	Kebbi	13	225	303	659
	Sokoto	376	226	391	647
	Zamfara	179	247	248	685
KEDC	Jigawa	532	235	247	599
	Kano	7,221	224	383	634
	Katsina	376	238	325	602
PHEDC	A/Ibom	78	244	610	677
	Bayelsa	-	247	501	628
	C/River	337	244	553	626
	Rivers	327	230	774	855
YEDC	Adamawa	2,258	227	375	635
	Borno	5,487	235	316	724
	Taraba	665	233	264	632
	Yobe	602	228	393	692

Table B.2: R2 Tariff Class ADMD Estimates

			Scenario ADMD (W)		
Distribution Company	State	Customers (Million)	Low	Medium	High
AEDC	Abuja FCT	0.13	934	996	1255
	Kogi	0.10	686	932	1078
	Nassarawa	0.12	607	932	1143
	Niger	0.11	488	641	1062
BEDC	Delta	0.31	762	939	1032
	Edo	0.13	1066	1201	1521
	Ekiti	0.07	411	635	1022
	Ondo	0.15	442	646	1082
EKEDC	Lagos	0.32	1063	1092	1319
EEDC	Abia	0.16	594	656	1139
	Anambra	0.29	705	721	1050
	Ebonyi	0.02	360	656	972
	Enugu	0.11	590	638	1045
	Imo	0.12	592	638	1065
IBEDC	Kwara	0.11	611	683	1112
	Ogun	0.26	516	668	1026
	Osun	0.26	499	664	998
	Oyo	0.37	611	627	1124
IKEDC	Lagos	0.51	1060	1095	1320
JEDC	Benue	0.07	653	991	1008
	Plateau	0.09	638	991	1125
	Bauchi	0.13	330	624	1052
	Gombe	0.09	306	708	1072
KDEDC	Kaduna	0.22	502	648	1071
	Kebbi	0.04	288	635	1100
	Sokoto	0.03	308	661	1083
	Zamfara	0.01	293	639	1093
KEDC	Jigawa	0.02	265	628	1107
	Kano	0.20	380	685	1032
	Katsina	0.06	351	693	1162
PHEDC	A/Ibom	0.11	610	697	1136
	Bayelsa	-	477	659	1025
	C/River	0.12	547	678	1049
	Rivers	0.32	751	790	1055
YEDC	Adamawa	0.05	721	656	1084
	Borno	0.05	331	633	1107
	Taraba	0.01	269	591	1060
	Yobe	0.02	349	661	1126

Table B.3: R1 Tariff Class ADMD Estimates

Distribution Company	State	Customers	Scenario ADMD (W) Low	Medium	High
AEDC	Abuja FCT	327	1385	2164	2248
	Kogi	17	1177	2126	2221
	Nassarawa	25	1165	2075	2257
	Niger	34	1194	2206	2365
BEDC	Delta	142	1204	2029	2189
	Edo	70	1471	2169	2163
	Ekiti	4	1119	2003	2044
	Ondo	20	1129	2020	2068
EKEDC	Lagos	1083	1505	2141	2258
EEDC	Abia	2	1155	2141	2192
	Anambra	18	1169	2095	2163
	Ebonyi	1	1138	2147	2154
	Enugu	427	1146	2030	2194
	Imo	200	1238	2068	2123
IBEDC	Kwara	13	1226	2084	2239
	Ogun	315	1054	2071	2183
	Osun	418	1168	2027	2271
	Oyo	116	1221	2222	2247
IKEDC	Lagos	167	1520	2146	2249
JEDC	Benue	44	1213	2055	2250
	Plateau	71	1237	2163	2238
	Bauchi	46	1300	2212	2344
	Gombe	69	1218	2137	2203
KDEDC	Kaduna	114	1162	2076	2184
	Kebbi	22	1216	2238	2276
	Sokoto	102	1182	2162	2299
	Zamfara	87	1201	2141	2350
KEDC	Jigawa	3	1193	2222	2345
	Kano	128	1161	2165	2233
	Katsina	29	1155	2336	2342
PHEDC	A/Ibom	43	1084	2040	2177
	Bayelsa	0	1195	2093	2229
	C/River	36	1202	2082	2124
	Rivers	576	1144	2052	2242
YEDC	Adamawa	50	1194	2219	2355
	Borno	79	1179	2186	2311
	Taraba	4	1241	2159	2320
	Yobe	18	1220	2241	2362

Table B. 4: R1 Tariff Class Peak Demand Estimates

		Scenario Peak Demand (MW)		
Distribution Company	**State**	**Low**	**Medium**	**High**
AEDC	Abuja FCT	0.3	1.4	1.5
	Kogi	0.8	0.8	2.2
	Nassarawa	0.3	0.3	0.7
	Niger	0.2	0.4	0.5
BEDC	Delta	0.3	1.0	1.2
	Edo	0.3	1.6	1.7
	Ekiti	0.0	0.1	0.1
	Ondo	0.1	0.3	0.4
EKEDC	Lagos	0.0	0.0	0.0
EEDC	Abia	0.1	0.3	0.4
	Anambra	0.0	0.0	0.0
	Ebonyi	0.2	0.3	0.5
	Enugu	0.2	0.7	0.7
	Imo	0.4	0.8	1.0
IBEDC	Kwara	0.0	0.0	0.0
	Ogun	0.6	1.3	1.7
	Osun	6.1	13.8	18.6
	Oyo	5.2	13.8	15.4
IKEDC	Lagos	0.0	0.0	0.0
JEDC	Benue	2.4	2.4	6.3
	Plateau	1.3	1.3	3.7
	Bauchi	1.1	1.7	2.9
	Gombe	1.6	2.3	4.6
KDEDC	Kaduna	0.0	0.0	0.1
	Kebbi	0.0	0.0	0.0
	Sokoto	0.1	0.1	0.2
	Zamfara	0.0	0.0	0.1
KEDC	Jigawa	0.1	0.1	0.3
	Kano	1.6	2.8	4.6
	Katsina	0.1	0.1	0.2
PHEDC	A/Ibom	0.0	0.0	0.1
	Bayelsa	0.0	0.0	0.0
	C/River	0.1	0.2	0.2
	Rivers	0.1	0.3	0.3
YEDC	Adamawa	0.5	0.8	1.4
	Borno	1.3	1.7	4.0
	Taraba	0.2	0.2	0.4
	Yobe	0.1	0.2	0.4

Table B. 5: R2 Tariff Class Peak Demand Estimates

		Scenario Peak Demand (MW)		
Distribution Company	**State**	**Low**	**Medium**	**High**
AEDC	Abuja FCT	125	133	168
	Kogi	50	66	104
	Nassarawa	55	74	139
	Niger	53	69	115
BEDC	Delta	239	294	323
	Edo	135	152	193
	Ekiti	29	45	72
	Ondo	65	95	160
EKEDC	Lagos	340	332	422
EEDC	Abia	97	107	186
	Anambra	201	206	299
	Ebonyi	8	15	22
	Enugu	67	72	118
	Imo	72	77	129
IBEDC	Kwara	68	76	125
	Ogun	136	176	270
	Osun	129	172	258
	Oyo	228	235	421
IKEDC	Lagos	518	559	685
JEDC	Benue	37	56	86
	Plateau	23	60	106
	Bauchi	22	42	71
	Gombe	40	93	141
KDEDC	Kaduna	112	145	240
	Kebbi	12	27	47
	Sokoto	9	19	31
	Zamfara	4	8	13
KEDC	Jigawa	6	15	26
	Kano	76	137	207
	Katsina	22	44	73
PHEDC	A/Ibom	69	79	128
	Bayelsa	0	0	0
	C/River	68	84	130
	Rivers	242	255	340
YEDC	Adamawa	36	33	55
	Borno	17	33	57
	Taraba	4	8	15
	Yobe	8	16	27

Table B.6: R3&R4 Tariff Class Peak Demand Estimates

		Peak Demand (MW)		
Distribution Company	**State**	**Low**	**Medium**	**High**
AEDC	Abuja FCT	24	37	39
	Kogi	1	2	2
	Nassarawa	1	3	3
	Niger	2	4	4
BEDC	Delta	9	16	17
	Edo	6	9	9
	Ekiti	0	0	0
	Ondo	1	2	2
EKEDC	Lagos	83	126	133
EEDC	Abia	0	0	0
	Anambra	1	2	2
	Ebonyi	0	0	0
	Enugu	25	44	47
	Imo	12	21	21
IBEDC	Kwara	1	1	1
	Ogun	17	33	34
	Osun	24	42	47
	Oyo	7	13	13
IKEDC	Lagos	13	18	19
JEDC	Benue	4	7	8
	Plateau	5	8	8
	Bauchi	3	5	5
	Gombe	3	5	5
KDEDC	Kaduna	7	12	13
	Kebbi	1	2	3
	Sokoto	6	11	12
	Zamfara	5	9	10
KEDC	Jigawa	0	0	0
	Kano	7	14	14
	Katsina	2	3	3
PHEDC	A/Ibom	3	5	5
	Bayelsa	0	0	0
	C/River	3	4	4
	Rivers	33	60	65
YEDC	Adamawa	3	6	6
	Borno	5	9	9
	Taraba	0	0	0
	Yobe	1	2	2

Table B.7: Commercial Sector Peak Demand (MW)

	Scenario		
	Low	Medium	High
Distribution Company			
Abuja	58	65	80
Benin	73	81	98
Eko	79	85	97
Enugu	85	96	113
Ibadan	58	64	78
Ikeja	128	135	154
Jos	37	42	47
Kaduna	60	68	84
Kano	29	32	35
Port Harcourt	47	54	59
Yola	18	19	20
Total	671	740	867

Table B. 8: Industrial Sector Peak Demand (MW)

	Scenario		
	Low	Medium	High
Distribution Company			
Abuja	115	138	158
Benin	81	90	103
Eko	204	231	254
Enugu	92	101	109
Ibadan	155	172	187
Ikeja	294	320	350
Jos	67	77	82
Kaduna	53	58	66
Kano	75	84	91
Port Harcourt	62	71	76
Yola	22	23	24
Total	1,219	1,365	1,500

Table B.9: Special Sector Peak Demand (MW)

	Scenario		
	Low	Medium	High
Distribution Company			
Abuja	14	15	16
Benin	17	18	20
Eko	16	18	19
Enugu	24	27	28
Ibadan	50	55	58
Ikeja	16	17	19
Jos	26	30	31
Kaduna	31	33	36
Kano	20	22	23
Port Harcourt	17	19	20
Yola	24	25	26
Total	256	279	296

Table B.10: Sectorial Energy Consumption

	Scenario		
	Low	Medium	High
Energy (TWh)			
Residential	12.5	15.3	21.8
Commercial	4.4	5.7	6.9
Industrial	9.4	11.6	15.8
Special	1.7	2.0	2.5
Contribution (%)			
Residential	45	44	47
Commercial	16	17	15
Industrial	34	33	34
Special	6	6	5

Appendix C
Power Network Data

Table C. 1: Nigeria Power Generation Stations

Power Station	Bus Number	Fuel Type	Units	Maximum Capacity (MW)
Afam_VI	83000	CCGT	4	728
Alaoji	83002	CCGT	4	480
Okpai	73002	CCGT	3	450
Olorunsogo_NIPP	13005	CCGT	6	758
Egbin	13002	Gas Fired Steam	6	1,320
Sapele	43004	Gas Fired Steam	6	528
Jebba	33004	Hydro	6	540
Kainji	33005	Hydro	8	760
Shiroro	33020	Hydro	4	600
AES	13002	OCGT	9	288
Afam_IV_V	83000	OCGT	20	804
Calabar	82004	OCGT	5	565
Delta	82017	OCGT	18	888
Gbarain	43005	OCGT	1	113
Geregu	43005	OCGT	3	414
Geregu_NIPP	82005	OCGT	3	444
Ibom	43002	OCGT	3	196
Ihovbor	13005	OCGT	4	452
Olorunsogo	82019	OCGT	8	336
Omoku	23002	OCGT	6	150
Omotosho	23002	OCGT	8	336
Omotosho_NIPP	12025	OCGT	2	500
Paras	82007	OCGT	6	54
Rivers	43004	OCGT	1	191
Sapele_NIPP	82007	OCGT	4	452
TransAmadi	43003	OCGT	4	100
			152	12,447

Table C. 2: Nigeria 330kV Test Network Buses

s/n	*Bus Number*	*Bus Name*	*s/n*	*Bus Number*	*Bus Name*
1	*13000*	*AJA 3*	31	*82017*	*YENAGOA 1*
2	*13001*	*AKANGBA 3*	32	*82018*	*AHOADA 1*
3	*13002*	*EGBIN 3*	33	*83000*	*AFAM IV 3*
4	*13003*	*IKEJA W 3*	34	*82004*	*CALABAR 1*
5	*13005*	*OLORUNSOGO3*	35	*82006*	*ITU 1*
6	*23000*	*AYEDE 3*	36	*73006*	*UGWUAJI 3*
7	*23001*	*OSOGBO 3*	37	*73004*	*ALIADE*
8	*23002*	*OMOTOSHO3*	38	*13028*	*ARIGBAJO*
9	*23003*	*GANMO 3*	39	*13026*	*OKE_ARO_ 3*
10	*33001*	*KATAMPE 3*	40	*13004*	*SAKETE 3*
11	*33002*	*BKEBBI 3*	41	*43011*	*EYEAN_3*
12	*33003*	*JEBBA T.S.3*	42	*33005*	*KAINJI G.S.3*
13	*33020*	*SHIRORO 3*	43	*33004*	*JEBBA G.S.3*
14	*35036*	*GWAGWALADA_3*	44	*43009*	*OBAJANA_3*
15	*42003*	*DELTA 1*	45	*43005*	*GEREGU*
16	*43000*	*AJAOKUTA 3*	46	*43003*	*DELTA IV 3*
17	*43008*	*LOKOJA_3*	47	*43004*	*SAPELE 3*
18	*43001*	*ALADJA 3*	48	*53001*	*KANO 3*
19	*43002*	*BENIN 3*	49	*63001*	*JOS 3*
20	*53000*	*KADUNA 3*	50	*63007*	*DAMATURU 3*
21	*63000*	*GOMBE 3*	51	*63006*	*JALINGO 3*
22	*63002*	*YOLA 3*	52	*73002*	*OKPAI 3*
23	*73000*	*NHAVEN 3*	53	*82028*	*OWERRI 1*
24	*73001*	*ONITSHA 3*	54	*82014*	*RIVERS_IPP*
25	*82000*	*AFAM 1*	55	*82022*	*GBARAIN UBIE*
26	*83002*	*ALAOJI 1*	56	*82019*	*OMOKU 1*
27	*82007*	*PHCT MAIN1*	57	*82026*	*ABA 1*
28	*73003*	*MAKURDI*	58	*82010*	*UYO 1*
29	*63005*	*MAIDUGURI 1*	59	*12025*	*IKORODU*
30	*82005*	*EKET 1*			

Table C. 3: Nigeria 330kV Test Network Lines

ID	Line	From Bus	To Bus	X(pu)	Smax
1	L1	13000	13002	0.004255	777.3
2	L2	13000	13002	0.004255	777.3
3	L3	13001	13003	0.005167	777.3
4	L4	13001	13003	0.005167	777.3
5	L5	13002	13003	0.005471	777.3
6	L6	13002	13026	0.005471	777.3
7	L7	13002	13026	0.005471	777.3
8	L8	13002	43002	0.06079	777.3
9	L9	13003	13004	0.021276	777.3
10	L10	13003	13005	0.023403	777.3
11	L11	13003	13026	0.005471	777.3
12	L12	13003	13026	0.005471	777.3
13	L13	13003	23001	0.075987	777.3
14	L14	13003	23002	0.024315	777.3
15	L15	13005	23000	0.018237	777.3
16	L16	23000	23001	0.034954	777.3
17	L17	23001	23003	0.014286	777.3
18	L18	23001	33003	0.04772	777.3
19	L19	23001	33003	0.04772	777.3
20	L20	23001	43002	0.076291	777.3
21	L21	23001	43011	0.042858	777.3
22	L22	23002	43002	0.015501	777.3
23	L23	23003	33003	0.033435	777.3
24	L24	33001	33020	0.066263	777.3
25	L25	33001	35036	0.021885	777.3
26	L26	33002	33005	0.094224	777.3
27	L27	33003	33004	0.002432	777.3
28	L28	33003	33004	0.002432	777.3
29	L29	33003	33005	0.02462	777.3
30	L30	33003	33005	0.02462	777.3
31	L31	33003	33020	0.074163	777.3
32	L32	33003	33020	0.074163	777.3
33	L33	33020	35036	0.044378	777.3
34	L34	33020	53000	0.029179	777.3
35	L35	33020	53000	0.029179	777.3
36	L36	35036	43008	0.053071	777.3
37	L37	35036	43008	0.053071	777.3
38	L38	35036	43009	0.053071	777.3
39	L39	42003	43002	0.240725	125.7
40	L40	43000	43002	0.05927	777.3
41	L41	43000	43002	0.05927	777.3
42	L42	43000	43005	0.000456	777.3
43	L43	43000	43005	0.000456	777.3
44	L44	43000	43008	0.014408	777.3
45	L45	43000	43008	0.014408	777.3
46	L46	43008	43009	0.014408	777.3
47	L47	43001	43003	0.009726	777.3
48	L48	43001	43004	0.019149	777.3
49	L49	43002	43003	0.012462	777.3
50	L50	43002	43004	0.015198	777.3
51	L51	43002	43004	0.015198	777.3
52	L52	43002	43004	0.015198	777.3
53	L53	43002	73001	0.041641	777.3
54	L54	43002	73001	0.041641	777.3
55	L55	53000	53001	0.069908	777.3
56	L56	53000	63001	0.059574	777.3

ID	*Line*	*From Bus*	*To Bus*	*X(pu)*	*Smax*
57	*L57*	*63000*	*63001*	*0.080242*	*777.3*
58	*L58*	*63000*	*63002*	*0.072948*	*777.3*
59	*L59*	*63000*	*63007*	*0.048631*	*777.3*
60	*L60*	*63002*	*63006*	*0.048631*	*777.3*
61	*L61*	*73000*	*73001*	*0.029179*	*777.3*
62	*L62*	*73001*	*73002*	*0.018237*	*777.3*
63	*L63*	*73001*	*73002*	*0.018237*	*777.3*
64	*L64*	*73001*	*83002*	*0.041945*	*777.3*
65	*L65*	*82000*	*83002*	*0.103489*	*125.7*
66	*L66*	*83002*	*82028*	*0.13467*	*125.7*
67	*L67*	*83002*	*82028*	*0.13467*	*125.7*
68	*L68*	*82000*	*82007*	*0.085041*	*125.7*
69	*L69*	*82000*	*82014*	*0.042521*	*125.7*
70	*L70*	*82007*	*82014*	*0.042521*	*125.7*
71	*L71*	*82017*	*82018*	*0.103489*	*125.7*
72	*L72*	*82017*	*82018*	*0.103489*	*125.7*
73	*L73*	*82017*	*82022*	*0.011249*	*125.7*
74	*L74*	*82017*	*82022*	*0.011249*	*125.7*
75	*L75*	*82018*	*82019*	*0.033747*	*125.7*
76	*L76*	*82018*	*82019*	*0.033747*	*125.7*
77	*L77*	*82018*	*82028*	*0.164233*	*125.7*
78	*L78*	*82018*	*82028*	*0.164233*	*125.7*
79	*L79*	*83000*	*83002*	*0.007598*	*777.3*
80	*L80*	*83000*	*83002*	*0.007598*	*777.3*
81	*L81*	*73000*	*73006*	*0.029179*	*777.3*
82	*L82*	*82004*	*82006*	*0.106549*	*125.7*
83	*L83*	*82006*	*82026*	*0.19213*	*125.7*
84	*L84*	*73006*	*73004*	*0.106549*	*777.3*
85	*L85*	*73004*	*73003*	*0.106549*	*777.3*
86	*L86*	*13028*	*23001*	*0.106549*	*777.3*
87	*L87*	*13028*	*23000*	*0.106549*	*777.3*
88	*L88*	*83002*	*82026*	*0.022498*	*125.7*
89	*L89*	*83002*	*82026*	*0.022498*	*125.7*
90	*L90*	*63005*	*63007*	*0.493914*	*777.3*
91	*L91*	*82005*	*82010*	*0.103489*	*125.7*
92	*L92*	*82005*	*82010*	*0.103489*	*125.7*
93	*L93*	*82006*	*82010*	*0.040496*	*125.7*
94	*L94*	*82006*	*82010*	*0.040496*	*125.7*
95	*L95*	*13002*	*12025*	*0.044995*	*125.7*
96	*L96*	*13002*	*12025*	*0.007598*	*125.7*

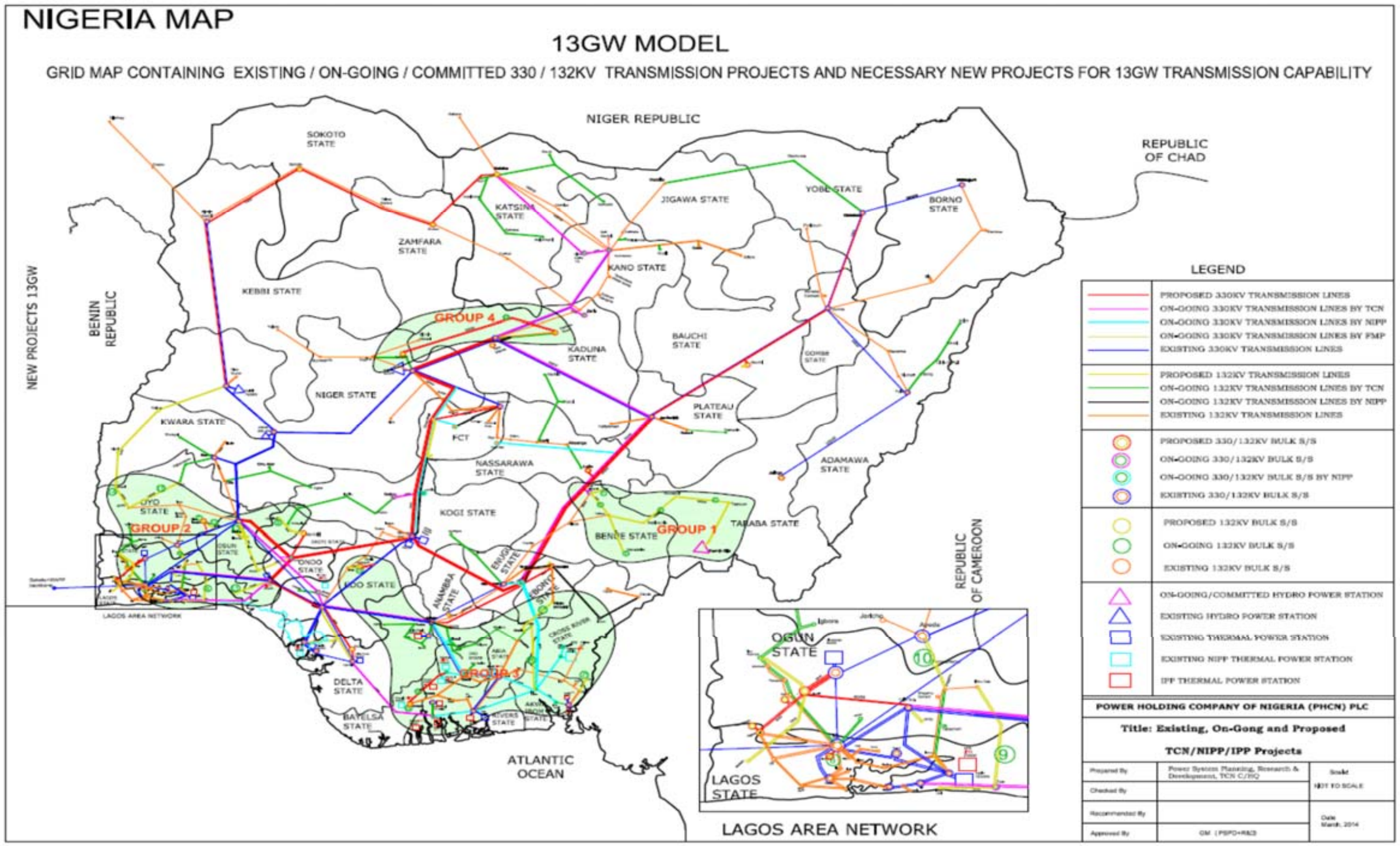

Figure C.1: Map of the Nigerian Transmission Grid

Appendix D
Maps

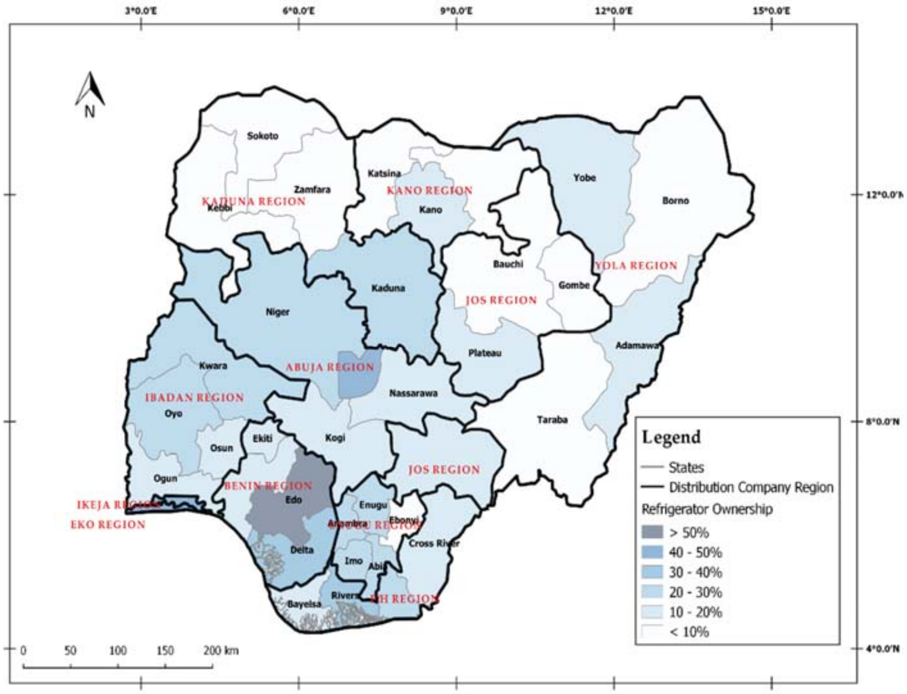

Figure D- 1: Domestic appliance ownership in Nigeria – Refrigerator

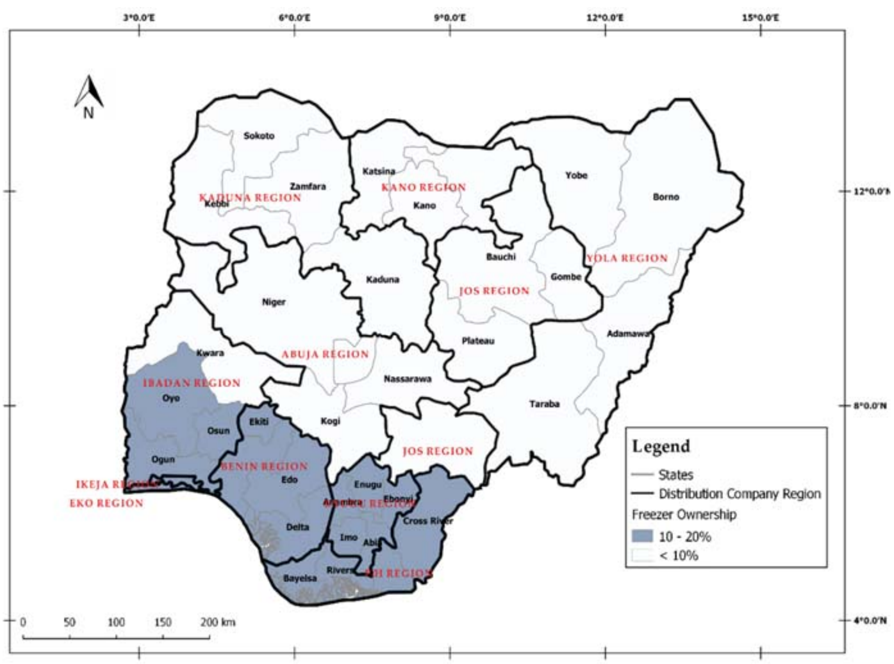

Figure D- 2: Domestic appliance ownership in Nigeria – Freezer

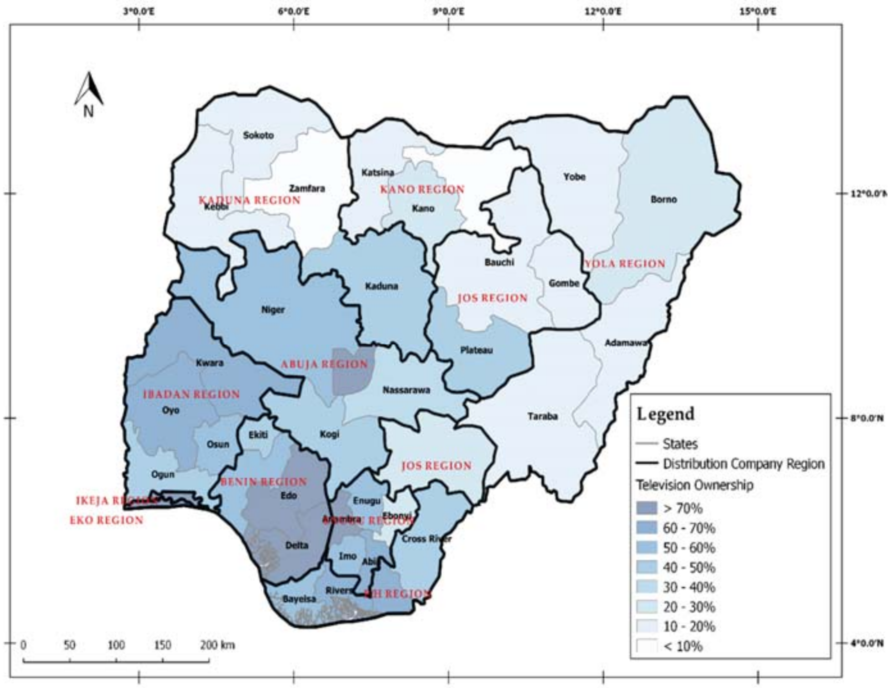

Figure D- 3: Domestic appliance ownership in Nigeria – Television

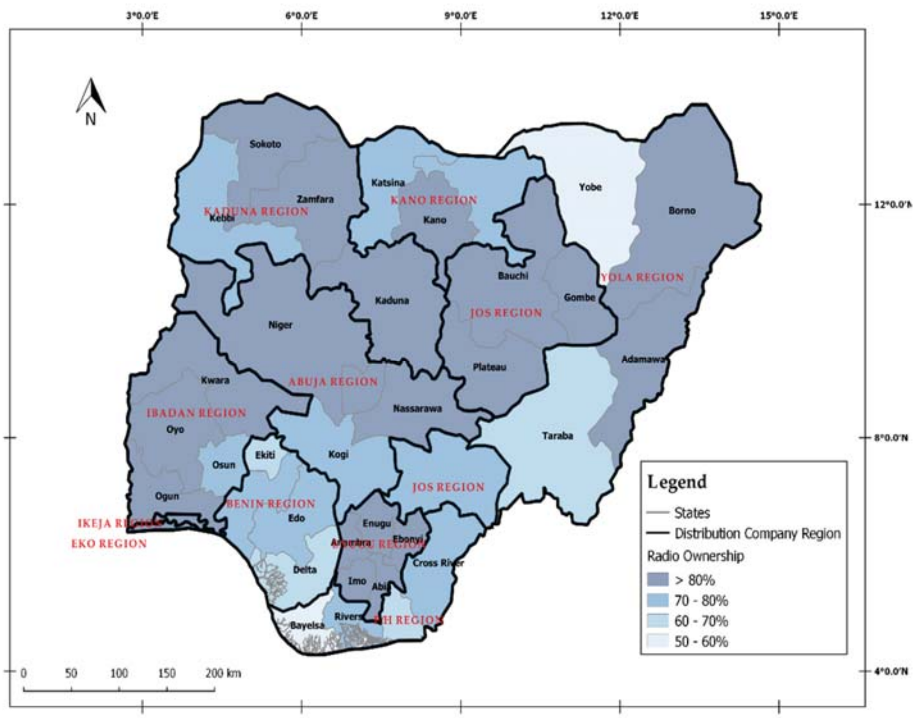

Figure D- 4: Domestic appliance ownership in Nigeria - Radio

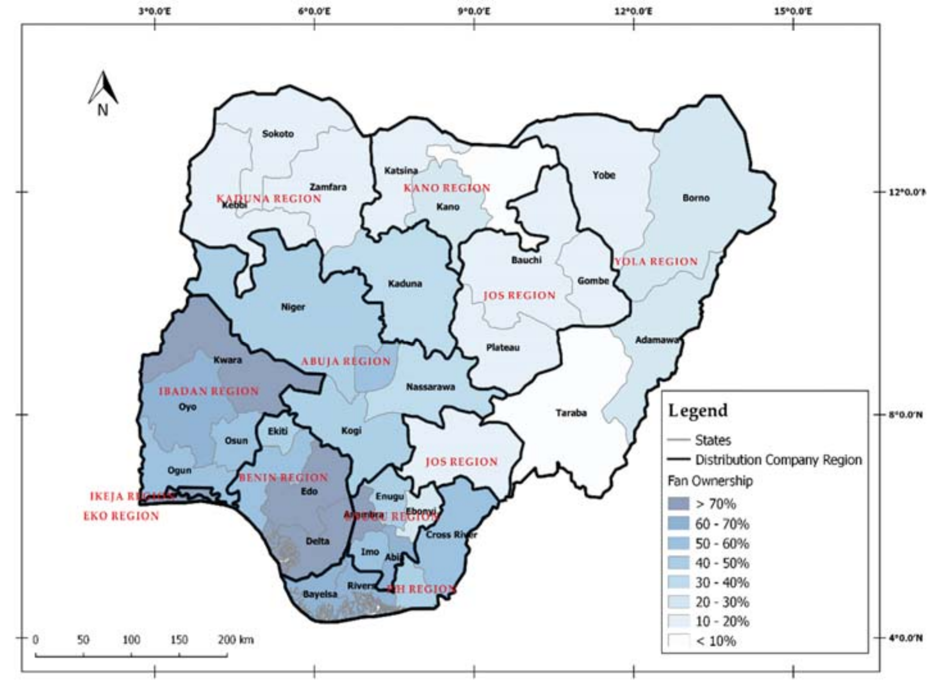

Figure D- 5: Domestic appliance ownership in Nigeria – Fan

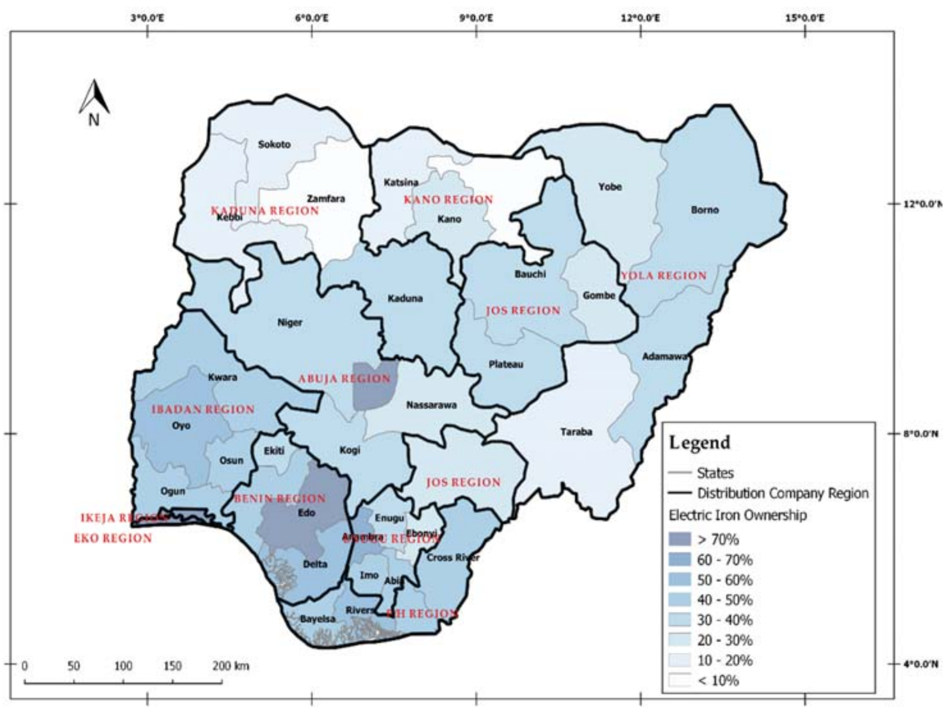

Figure D- 6: Domestic appliance ownership in Nigeria - Electric Iron

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